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Analysis and Prediction of Readmissions at a Large University Medical Center

ABSTRACT

Patient safety is one of the key goals of hospitals and health systems in the United States healthcare landscape today. One of the determinants of high quality and safe patient care is the rate of readmissions of a hospital. Readmissions occur when patients are admitted to a hospital within a specified period of time after a prior admission. The rate of these readmissions is also tied to hospital reimbursement and Medicare rating. Thus reducing readmissions is of paramount importance of health systems nationwide. This study will use three different analytical approaches to predict readmissions by using a large dataset extracted from the electronic medical records (EMR) of a large hospital system.

INTRODUCTION AND REVIEW OF THE LITERATURE

Readmissions are defined as the necessity of an inpatient medical treatment of a patient after a recent hospitalization. Most common metrics which hospitals are held accountable for are 7 day, 30 day and 90 day readmissions. These each indicate an admission within 7, 30 or 90 days after a recent discharge from a hospital. Hospitals, payors and the Centers of Medicare and Medicaid Services (CMS) track hospital readmissions closely and adjust payments to hospitals according to their readmissions rates.[1,2]. This is part of the policy changes which occurred with the advent of the Affordable Care Act and the initiation of the value based purchasing vs the more traditional fee for service models. [4]

However, beyond payments, readmissions are indicative of a failure of the healthcare system to appropriately recognize patient illness, categorize severity of illness, provide appropriate treatment and follow up and take socioeconomic factors or the patient into consideration. Almost all hospitals in the United States have some sort of a readmission reduction task force aimed at identifying deficiencies in the system which are contributing to their readmissions. [2,3]

Almost every Electronic Medical Record (EMR) has the ability to generate some form of a risk assessment for readmissions. This is based on various datapoints which are present in their health record as well as their demographic information. These are based on proprietary algorithms which are are validated internally, however these may not necessarily be accurately reflective of the local demographics of a hospital or be necessarily adaptable to a hospital’s need. [4]

Various methodologies have been adopted across the healthcare platform, which has allowed some significant decreases in readmissions. This was recently studied by Wasfy al, examining the reduction in readmission after the passage of the readmission reduction act. They show a reduction of an average of 84 readmissions per 10000 patients annually across all 2868 hospitals serving medicare patients[5].

One of the most promising new avenues has been to develop predictive tools which can be augmented and scaled to off readmission risk assessment and are more tailored to the individual hospital or health system. This was studied extensively in heart failure [6] and myocardial infarction [7]. Big Data analytics should be able to give scalable algorithms which hospitals can implement and integrate into their respective workflows. [8, 9]

Multiple papers recently published have tried to implement deep learning algorithms to data extracted from EMRs to predict 30 day readmissions. [10]. In the paper by Wang H, Predicting Hospital Readmissions via Cost-Sensitive Deep Learning, the authors compare 6 deep learning algorithms in terms of their accuracy to predict 30 day readmissions. Their results do show an accuracy between 61 and 92% and a sensitivity between 0 and 45%. This study was conducted on extracts from two different hospitals and each hospital did achieve a different sensitivity despite being trained on the same algorithm. [10]

In the paper by Rajkomar et al, Scalable and accurate deep learning with electronic health records, published in Nature Digital Medicine, they use a deep learning algorithm to predict hospital readmission among other outcomes. They achieve a 76% accuracy with their model, however, do not report sensitivity in this study. [11]

Various logistic regression model had been used and Nguyen et al compared three models to a fourth model they had developed in their paper Prediciting all cause readmissions using the electronic health record data from the entire hospitalization: Model development and comparison. They were able to prove that the comprehensive model they sued performed better than the standard models previously published at 69% accuracy. The sensitivity was not published in this paper either. [12]

In this study we propose to use an extract of the EMR at a large university medical center to develop a predictive algorithm for 30 day readmissions by using a combination of logistic regression and random forest classifier. These are easily scalable and easy to implement and adapt to local variables, thus they may be more easily approachable to community hospitals and intergaratable into their own quality improvement initiatives. This also is a novel approach which has not been studied in the past and may offer a differential insight into the prediction dilemma of readmissions. In the final part of the paper, an attempt will be made to develop an ARMA model to predict total readmissions as these are considered as time series data points. This is important as it may help identify temporal, seasonal or provider specific characteristics which can be mitigated to reduce overall readmissions.

DATA

The Data for this research study was obtained from the EMR of the George Washington University Hospital. The extract was performed through a software called MIDAS. This is a healthcare quality management software which compiles data from the EMR, insurance claims and reviews. It is also used internally to track adverse outcomes and manage internal document reviews. The extract was performed on all patients admitted from January 2008 to December 2018, resulting in 204554 patients admitted in that 10 year period. There was a total of 262 features available for review. These features are divided into:

1. Patient Demographics: Age, Race, Sex, Religion, family status, Zip code, language, citizenship.
2. Admission characteristics: location they were admitted from, date and time of admission and discharge, discharge location, total length of stay, admitting team, discharging team, and admission diagnosis
3. Illness characteristics: Admission diagnosis, other diagnoses related to it, procedures required, consults called
4. Financial and billing characteristics: including the total amount billed, amount collected, diagnosis-related group (DRG), insurance
5. MIDAS specific extracts including mortality adjustment risks, readmission risk scores, and disease severity scores. These were available to only a subset of the patients.

There were no patient identifiers in this dataset. This dataset extract was obtained after an Institutional Board Review (IRB) deemed this study as exempt from needing a full IRB approval and granting an IRB exemption on the basis of quality improvement project designation.

Two other fields were also included in this dataset. A medical record number (or MRN) which serves as a unique patient identifier and a financial number which is a unique string of numbers characterizing every admission. Thus if one patient is admitted twice to the hospital their medical record number will be the same, but they will have a different financial number. These numbers cannot be traced back to the hospital except through particular access to the EMR at GWUH. Thus, these two numbers could serve as unique identifiers for each patient and each encounter respectively.

EXPLORATORY DATA ANALYSIS

An exploratory data analysis was conducted to evaluate the data and understand the best approach to constructing a comprehensive model for predicting readmissions. All of the incomplete records were removed and the total number of patient encounters was then 154946 with 293 features.

The first thing which was done was to add a variable called readmission. This is a binary variable indicating whether a patient was readmitted within 30 day of discharge (1) or not (0). The construction of this variable was through Alteryx where if the same MRN was admitted twice within a 30 day period then a (1) was assigned to the second admission. This resulted in 13585 readmissions or an 8.7% readmissions rate.

The second set of calculated variables which were added to the data were targeting the physician and team characteristics affecting a patient’s admission and discharge. In theory, physician teams who are busier would have more difficulty performing as well when doing an admission or a dsicharge. Thus if the team is not vigilant, the discharge process may not be done correctly thus prompting a readmission. To start , using Alteryx, the number of admissions and discharges each team performed each day was calculated. The higher the number of admissions and discharges performed the busier a team is. These were then added to every patient. For a particular patient, the number of admissions and discharges done by the admitting and discharging teams on the day of admission (start date) and discharge date(end date) were added.

The total number of patients every team carried for the period the patient was under their care. This is also a reflection of the workload each team has, and may have an effect on the readmission rate of the patients. This was calculated by accounting for every day a patient was in the hospital and counting the total number of patients under the care of their team.

Starting with patient characteristics the age distribution is a normal distribution with a mean of 43.4 and a standard deviation of 12 years. A slight predominance of women was noted with 56% of Sex reported as female. The zip code distribution shows patients do come from every state in the US, however the majority of the admissions here are from the District of Columbia and Maryland.

The Length of Stay (LOS) of patients varied from 0 to greater than 365 days. A histogram of the LOS is provided and shows a left skewed curve with most LOS between 0 and 4 days. Medicine had the highest number of admissions at 41842 without subspecialty medical cases, and a combined of 72195 cases. Surgical subspecialties and obstetrics and gynecology were the second and third busiest services at GWUH.

The patient’s admitting diagnosis as well as all of the other diagnosis are summarized in terms of their ICD9 (until September 2014) and ICD 10 codes. These are not signficant on their own as these are the detailed codes for the diagnoses and are difficult to interpret. Thus the Elixhauser disease severity index was used to transform these ICD9/10 codes to easy to interpret 21 disease buckets, as well as a disease severity index score which assigns a weighted value to the patients according to how ill they are. [13] This is a validated tool and the R algorithm was used to transform the ICD 10 codes into these buckets. In addition the different procedures and consults were also included in this dataset. The total number of procedures and consults was calculated and thought to summarize the course of a patient’s hospital stay. To my knowledge there is no tool to combine the procedures and consults into buckets to streamline the analysis. Thus the totals was used.

The average total number of procedures patients receive is 2, with a range from 0 to 20. The distribution is also left skewed. On average patients receive 8 diagnoses, with a similar left skewed distribution, but a much wider range from 1 to 40 diagnoses. Similarly, the disease severity illness shows a left skewed distribution.

The main payers were also summarized and indicate an almost equal distribution of Medicaid and Medicare. Other private insurances were also represented, however to a lesser extent. Charges filed to insurance companies varied from 0 to greater than 4.5 million dollars. The cost for patients was not available for all years and thus this variable was dropped from further analysis.

METHODS

The data was obtained from the quality department of the hospital in excel format. The initial data wrangling and cleaning was performed using Alteryx. This is a data analysis interface which uses R as the backend for analysis, however, makes data cleaning and rearrangement easier and more user friendly. It also allows for large excel files to be transformed to Alteryx databases which run faster on the platform and thus the modifications tend to be faster. Alteryx is available to download online and allows free access to academic centers through their Alteryx for good program. All Alteryx workbooks are available as supplementary material. Tableau was used for all visualizations. All tableau visualizations are available as supplementary material. The main data analysis was carried out in R. The R code is available as supplementary material. The time series analysis was carried out in Python 3.7 and the code is also available.

After the initial data cleaning and feature engineering discussed above was completed in Alteryx, the data was loaded into R and a series of gradient descent/elastic net logistic regressions were carried out in an attempt to identify a suitable predictive model as well as a way of feature selection. This was carried out after a model.matrix was run to create a very large design matrix. Next a series of Random Forests were constructed with the features identified above to generate a predictive classification model for readmissions.

None of the above models were able to take the dates and the continuous time series nature of the data into account. Thus a time series analysis was carried out and multiple ARMA models were constructed and predictions calculated and compared, and one final model selected. The data used here was an extract of only the total number of readmissions on a daily basis over the study’s time period.

RESULTS

The first model used was a regression model on the original dataset. This included all of the features and the 80% of the rows of the data. This was to have a test data set for evaluating the accuracy of the model. The model was an elastic net model with hyperparameters chosen after a grid search was conducted. The model was used to generate a table with all of the coefficients which are non zero, and then transform to a csv file. The initial model had a low RMSE of 1 however its prediction despite having an excellent accuracy had a very low specificity of 18%

Next these non zero coefficients were used to generate a secondary reduced dataset and remove the non important features. This dataset was then used to generate a secondary elastic net model to evaluate the accuracy of the logarithmic regression model as well as evaluate the importance of the features when model is created with lower number of features.

The new model was constructed again using a cross validated elastic net tuned after a grid search through glmnet. The coefficients were also saved in a different dataset in case a repeat reduction would be necessary. The new model’s performance was very similar to the initial one. Thus, all of the significant variables from this model were picked and a third logistic regression constructed and similarly tested. The RMSE, overall accuracy and sensitivity of the three models are summarized in table below;

|  |  |  |  |
| --- | --- | --- | --- |
| Model | Accuracy | Specificity | RMSE |
| Model1 | 0.921 | 0.15 | 1.07 |
| Model2 | 0.924 | 0.15 | 0.0771 |
| Model3 | 0.916 | 0.123 | 0.071 |

Even though the third model does provide a lower RMSE and similar accuracy it does not provide a high sensitivity, and it is indeed lower than what other studies had found.

The attributes which were included in the last model had been the ones whose coefficients were the highest. Thus, these were used to develop the random forest classifier. The features used are summarized below;

|  |  |
| --- | --- |
| Admitting\_Source\_OUTPATIENT\_CLINIC | Facility\_DC\_Disposition\_DISCH\_TO\_HOSPICE\_HOME |
| Admitting\_Source\_TRANS\_SKILLED\_NURSING\_FACILITY | Discharge\_APR\_DRG\_MDC16 |
| Admitting\_Loc\_HOSP\_ER\_HOLDING | Discharge\_APR\_DRG\_MDC18 |
| Admitting\_Source\_ROUTINE\_IP\_ADMISSION\_\_UNSCH | Discharge\_APR\_DRG\_MDC23 |
| Admitting\_Loc\_GWU\_PACU | Discharge\_APR\_DRG\_MDC11 |
| Admitting\_Loc\_GWU\_5\_SO\_ONCOLOGY | CDB\_APR\_DRG\_Acute\_Care\_Expected\_Mortality |
| Admitting\_Service\_Code\_NEU | DRG\_MDC\_NO\_17 |
| Principal\_Payer\_H\_S\_C\_S\_N\_\_MCAID\_HMO | CDB\_APR\_DRG\_All\_Inpatient\_Expected\_Mortality |
| Principal\_Payer\_AMERIHEALTH\_MCAID | rheumd |
| Principal\_Payer\_MEDICAID | solidtum |
| Principal\_Payer\_NON\_CONTRCTD\_HMO\_PPO | lymph |
| Principal\_Payer\_Type\_SELF\_PAY\_ADMIT | diabc |
| Principal\_Payer\_MEDICARE\_PT\_B\_IP | pvd |
| Principal\_Payer\_AMERIHEALTH\_ALLNCE | metacanc |

The random model classifier was trained on the same 80% of the data and was run over 500 trees. The mean decrease of Gini was then extracted to evaluate the feature importance in this dataset;

|  |  |
| --- | --- |
| Features | MeanDecreaseGini |
| CDB\_APR\_DRG\_All\_Inpatient\_Expected\_Mortality | 1056.624 |
| Discharge\_APR\_DRG\_MDC23 | 918.1059 |
| CDB\_APR\_DRG\_Acute\_Care\_Expected\_Mortality | 712.5953 |
| Admitting\_Source\_ROUTINE\_IP\_ADMISSION\_\_UNSCHEDULED\_ | 139.4197 |
| Discharge\_APR\_DRG\_MDC18 | 111.394 |
| DRG\_MDC\_NO\_17 | 109.4892 |
| diabc | 95.33324 |
| Admitting\_Loc\_GWU\_5\_SO\_ONCOLOGY | 93.28339 |
| Admitting\_Loc\_GWU\_PACU | 81.13076 |
| Principal\_Payer\_MEDICAID | 67.72274 |
| solidtum | 65.01218 |
| lymph | 61.86407 |
| metacanc | 60.12244 |
| pvd | 55.80766 |
| Principal\_Payer\_AMERIHEALTH\_MCAID | 49.59602 |
| Discharge\_APR\_DRG\_MDC16 | 46.64945 |
| Admitting\_Service\_Code\_NEU | 45.87765 |
| rheumd | 43.13089 |
| Discharge\_APR\_DRG\_MDC11 | 35.91112 |
| Principal\_Payer\_MEDICARE\_PT\_B\_IP | 30.36313 |
| Principal\_Payer\_AMERIHEALTH\_ALLNCE | 22.22456 |
| Principal\_Payer\_Type\_SELF\_PAY\_ADMIT | 21.51761 |
| Facility\_DC\_Disposition\_DISCH\_TO\_HOSPICE\_HOME\_\_CONTINUOUS\_CARE\_ | 15.36546 |
| Principal\_Payer\_H\_S\_C\_S\_N\_\_MCAID\_HMO | 12.46622 |
| Admitting\_Source\_OUTPATIENT\_CLINIC | 11.67475 |
| Admitting\_Loc\_HOSP\_ER\_HOLDING | 9.309824 |
| Principal\_Payer\_NON\_CONTRCTD\_HMO\_PPO | 7.15871 |
| Admitting\_Source\_TRANS\_SKILLED\_NURSING\_FACILITY | 3.829835 |

The confusion matrix for this model is included below:

Confusion Matrix and Statistics

Reference

Prediction 0 1

0 28123 2344

1 158 364

Accuracy : 0.9193

95% CI : (0.9162, 0.9223)

No Information Rate : 0.9126

P-Value [Acc > NIR] : 1.459e-05

Kappa : 0.2029

Mcnemar's Test P-Value : < 2.2e-16

Sensitivity : 0.9944

Specificity : 0.1344

Pos Pred Value : 0.9231

Neg Pred Value : 0.6973

Prevalence : 0.9126

Detection Rate : 0.9075

Detection Prevalence : 0.9832

Balanced Accuracy : 0.5644

To study the total number of readmissions and try to predict the average total number of readmissions per day. To do that the total number of readmissions was calculated and the data was evaluated for stationarity. The data did pass the ADF-Fuller test, however, the autocorrelation plot did not suggest a stationary process. Thus the first differenced dataset was used and confirmed that it is stationary by the ADF test which was -19.47. The mean and autocorrelation plot are illustrated below;

A screenshot of a social media post

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Description automatically generated

This stationary process was then modeled. A generalized partial autocorrelation function was used to estimate the order of the ARMA model. The GPAC table is illustrated below;

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
| 0 | -0.444 | -0.327 | -0.216 | -0.181 | -0.249 | -0.282 | -0.141 | -0.052 | -0.043 |
| 1 | 0.149 | -0.091 | 0.066 | 0.13 | -0.05 | -0.238 | 0.074 | 0.039 | 0.046 |
| 2 | -0.448 | 0.08 | 1.439 | -1.082 | -25.854 | 1.03 | -0.787 | -0.525 | -0.029 |
| 3 | -0.591 | -3.966 | 0.912 | -0.86 | 5.839 | 1.555 | -0.972 | 1.745 | -0.38 |
| 4 | 3.769 | 1.096 | -4.017 | -1.024 | 0.76 | 0.701 | -13.367 | -0.789 | -1.548 |
| 5 | -0.072 | -1.732 | 0.217 | 1.197 | 0.444 | 2.857 | -1.085 | -0.097 | -3.824 |
| 6 | 23.879 | 1.002 | -11.468 | -0.996 | -10.657 | 0.966 | -1.758 | -1.912 | 0.924 |
| 7 | -0.018 | -0.363 | -0.174 | -0.031 | -0.795 | -1.144 | -5.127 | 1.399 | 0.979 |
| 8 | 20.591 | 0.984 | 2.222 | -0.543 | 1.04 | 22.661 | -1.054 | 0.562 | -3.147 |

Given that the GPAC table did not generate a clear candidate of the model order to be selected, except for an autoregressive process (AR) of 7 and a moving average order (MA) of 1. Thus a grid search was conducted to evaluate models with all orders. This was carried out with an iterative process which included a try/except/pass to facilitate the progression. Given that the stasmodel package used sometimes stalls and is well documented to not achieve convergence a number of warning would appear during this process, however a final table of all AICs and Q values for all orders can be calculated.

From the prior iteration, two models were chosen to be tested. A model with an AR order of 4 and an MA order of 8 and also a second model of AR order of 8 and an MA model of 6. The fit of both models is illustrated below;

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Model1: AR=4 and MA = 8

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Model2:AR=8, MA=6

The autocorrelation function for both models is very similar to an impulse response: A screenshot of a social media post

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However, neither of the models are statistically signficant as both produce a Q value that is higher than the chi square critical value. Thus neither of the models would be a reliable model to predict overall readmissions to the hospital.

ANALYSIS

The presented dataset is a complex dataset which is an extract from the EMR of the GWUH. This is an extract that is not often reported in the literature when modeling is used. Most studies reviewed use text rich EMR extracts which are cumbersome to use, and models are difficult to implement. MIDAS extracts on another hand, are precoded, easy to extract and readily available. Thus easy to implement once a model is identified.

The statistical approach is also not used in prior studies. This is an easier model to implement and could be modified to specific service lines or hospitals, as features can change. Most models use a predetermined set of features which are extracted. A pipeline built in this model would allow personalization and feature importance analysis.

The regression models were promising with excellent accuracy and RMSE. However, their low specificity precludes them from being useful in the clinical setting. The goal is to be able to identify correctly every single patient who is at risk for admission. Thus, a 15% specificity is not sustainable. It may make a difference in the total number of readmissions, and if half of these 15% correctly identified patients are prevented from being readmitted, that is more than enough to comply with latest CMS guidelines, and thus not lose the compensation associated with it.

The random forest model is robust in its accuracy but failed to achieve a higher specificity. This could be related to the lower number of trees, and with higher computing capacity, one could potentially run 5000 trees and compare the model to the one at hand.

The other argument here for improving specificity may be to enrich the data with positive cases and allow the model to learn the behavior of the readmits. This can be done by using an over-Under resampling, or a more advanced algorithm, like ROSE which allows for data expansion and enrichment. That could be one way to potentially improve the specificity.

The analysis of the total number of readmissions also provides a clear path towards understanding the exact nature of the temporal relationships of readmissions in general. There was no seasonality in the total readmissions data. The first differenced data was reliable in providing excellent performing models with very low Q values and excellent AICs. Also the autocorrelation plots of the residuals of the models does indicate an impulse response. The fact that the Chi-Square test was negative may have been related to the very low degrees of freedom given that the orders of the models chosen were large. Options to move forward with the analysis is to try the model on ordered subsets of the data and evaluate these. Alternatively, one can prospectively study the model and fine tune the hyperparamters that way.

CONCLUSION

This study helped understand the wealth of data available from an excerpt of the EMR at GWUH. This was also helpful to evaluate a new technique to study readmissions. This paper is valuable as it offers the ability to evaluate and appreciate random forest classifiers for evaluation of readmissions.

Despite excellent accuracies in prediction, the models were not helpful in achieving high specificities. This could be remediated perhaps by studying other models. An example would be a long short term memory (LSTM) neural networks which should help evaluate the temporal relationship as well as serve as a deep learning technique to predict discharges. The literature reported so far includes only small improvement to the specificity and a decrease in the overall accuracy of prediction.

These models can also be tested for many other outcomes that are available for study from this database. An example would be predicting patients who are being discharged early and predicting overall census, length of stay, and even mortality. This provides hospitals with the opportunity to identify areas of improvement, evaluate specific factors leading to undesired outcomes and improve the overall quality of the care provided. Herein lies the benefit of this study. It establishes a possible pipeline and provides a direction for future work on the many other variables which can be predicted through a dataset such as this one.

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