Sreenivasula R Gajjala. Longitudinal Analysis of Readmission Risk Using Machine Learning. A Master's Project for the M.S. in I.S. degree. November, 2015. 30 pages. Advisor: David Gotz

Unnecessary hospital readmissions are a major problem impacting millions of patients and costing billions of dollars per year. Unfortunately, accurate assessment of readmission risk remains an open problem. In this study, several methods and tools for readmission prediction were developed using UNC hospital data available from April 1, 2014 to November 1, 2014. This study investigated the change in readmission risk for patients over time to explore at which times high-risk patients can be most effectively identified. Toward this goal, multiple Machine Learning models of hospital readmission using patient history prior to admission and comparing them with baseline model which uses data during hospitalization were developed. The results of this study find that patients history did not produce better predictive performance than the baseline model that considered just hospitalization data. However, the dataset considered is small and results may not generalize to large data sets over longer period of time.

Headings:

Electronic Health Records

Patient Readmission

Machine Learning

Predictive models

LONGITUDINAL ANALYSIS OF READMISSION RISK USING MACHINE LEARNING

by
Sreenivasula R Gajjala

A Master's paper submitted to the faculty
of the School of Information and Library Science
of the University of North Carolina at Chapel Hill
in partial fulfillment of the requirements
for the degree of Master of Science in
Information Science.

Chapel Hill, North Carolina

November 2015

Approved by

____

David Gotz

Table of Contents

1. Introduction

Nationwide, 30-day hospital readmission rates approach 20% and unplanned rehospitalizations are estimated to cost Medicare $17.4 billion annually (Jencks et al., 2009). Moreover, these costs are expected to increase as the population ages. Because of the skyrocketing costs of hospital readmissions, in October 2012 the Centers for Medicare and Medicaid Services (CMS) started assessing financial penalties to hospitals with high readmission rates. More than 2,200 hospitals faced some level of penalty in the first year, with penalties amounting to approximately $125,000 per hospital on average and $280 million total (CMS 2012). Preventable readmissions are a top priority for many hospitals in the United States. By addressing the critical “voltage drop” in care that occurs when patients transition from hospital to home, hospital transition programs (HTPs) have been shown to reduce preventable hospital readmissions (Balaban et al., 2008). HTPs commonly include bundles of interventions such as medication reconciliation by pharmacists, post-discharge phone calls, nurse home visits, and home telemonitoring for patients. However, enrolling every hospitalized patient into a one-size fits all HTP, independent of readmission risk, may not be a sustainable and cost-effective solution for reducing readmissions. For example, among hospitals which developed successful HTPs in the context of research studies, 11 of 13 (85%) were subsequently discontinued due to financial constraints (Seow et al., 2006). Efficiently allocating limited and costly resources to patients who will benefit most is key for HTPs to be a long-term solution (Arbaje et al., 2008). Therefore, it is critical to develop tools that accurately identify which hospitalized patients are at highest risk for readmission and why—so that HTP interventions can be tailored for each unique patient's needs and individual risk factors.

2. **Research Questions:**

While most efforts at readmission risk analysis focus on assessing risk at the time of discharge, this study tests the hypothesis that the large volume of patient medical data known about a patient earlier in her/his medical history can be highly informative to support earlier assessments. This can help understanding risk evolves over time for specific patient subgroups can help support the design of more effective risk reduction programs.

Specific Aim #1: Patient cohort identification, characterization, and outcome modeling

For this study, data from from CDW-H managed by NC TraCS for three specific conditions that result in large numbers of hospitalizations: Chronic Obstructive Pulmonary Disease, Heart failure and Diabetes is used. For each condition, data of patients that have medical histories, both outpatient and inpatient, within CDW-H was acquired. Procedures, diagnoses, medications, labs, and demographics for the patients that meet inclusion criteria were considered. For those cohorts, study develops comprehensive descriptive statistics and define a small set of condition-specific, quantifiable outcome measures.

Specific Aim #2: Modeling, analysis, and evaluation

For each condition (COPD, HF, DIAB), models were generated by using patient data from four time intervals namely 15 days, 30 days, 45 days and 60 days prior to hospital admission. These models were compared to the baseline model generated from data during hospitalization.

3. Literature Review

The primary objective of this review is to explore and summarize readmission risk prediction models, data extraction and feature selection, and performance and evaluation of these models in existing literature. In most of them, readmission meant the patients getting admitted again within 30 days of their initial discharge. Most patients, when they are discharged from the hospital, assume they won't be readmitted. Unfortunately, that is not the case, especially with specific populations such as geriatric patients with CHF and COPD. The highest hospital readmission rates have been observed in patients with these conditions (Arian Hosseinzadeh, Masoumeh Izadi, Aman Verma, Doina Precup, and David Buckeridge 2013). Readmissions is a growing, urgent challenge with most hospitals attempting to address this problem on a priority basis. Preliminary findings suggest reducing readmission risks reduce medical costs and improve health outcomes. Based on 2005 data of Medicare beneficiaries, it has been estimated that 12.5% of Medicare admissions due to CHF were followed by readmission within 15 days, accounting for expenses of approximately $590 million (Kiyana Zolfaghar et al., 2013). A study conducted by the Medicare Payment Advisory Committee (MedPAC) reported that 17.6% of hospital admissions resulted in readmissions with 76%

of those as potentially unavoidable (Futoma, J., Morris, J., and Lucas, J. 2015). The Patient Protection and Affordable Care Act (PPACA) penalizes hospitals with high readmission rate through a program called the Hospital Readmission Reduction Program (Futoma, J., Morris, J., and Lucas, J. 2015). In turn, this is ushering in new business models in health care. Financial implications of accurately predicting hospital readmission rates are huge. However, developing such predictive models is a challenging process.

3.1 Feature Selection and Feature Elimination

Methods to predict hospital readmission risk are in great demand among healthcare organizations. A lot of research is being conducted to explore a plethora of statistical techniques and machine learning models for risk prediction. A wide variety of data sources are being used for these models including patient demographics, social characteristics, medications, procedures, diagnostic-related groups, laboratory tests, claims data and billing codes. Some researches explicitly use administrative data (He, D., Mathews, S. C., Kalloo, A. N., & Hutfless, S. 2014) and ICD-10 data (Futoma, J., Morris, J., and Lucas, J. 2015). The information is sourced and extracted from electronic health records and socio economic data available at National Inpatient Sample (NIS). Number of features selected in the models ranged from 20 (Arian Hosseinzadeh et al., 2013) to several thousands, with the number of patients whose data was analyzed ranging from thousands to millions (Kiyana Zolfaghar et al.,2013). Their data was sourced from United States, New Zealand (Futoma, J., Morris, J., and Lucas, J. 2015) and Australia (Tran, T., Luo, W., Phung, D., Gupta, S., Rana, S., Kennedy, R. L., ... & Venkatesh, S. 2014). Features included sociodemographic factors, health conditions, disease parameters, hospital care quality parameters, and a diverse set of health care providers-specific variables. In most cases, features were grouped into categories such as sociodemographic, vital signs, laboratory tests, discharge codes, medical comorbidity and length of stay. Some models analyzed features at different times of hospital stay, like pre-admission, post-admission, pre-discharge and post-discharge and used different features for their models (Vivek R Rao, Kiyana Zolfaghar, David K. Hazel,Vani Mandava,Senjuti Basu Roy and Ankur Teredesai 2014). For instance, at the time of admission the typically available information is patient history data and current vital signs. Over time, more data like laboratory test results, diagnosis codes are available which impact model accuracy. Collating and aggregating the data proves to be a challenge, as does framing the problem as a classical machine learning problem because of heterogeneity and complexity in the data. In most approaches, each visit was considered an instance and most informative aspects for prediction are ICD 9/10 codes (Futoma et al., 2015) and demographic features. Some models filtered out data about the patient's death, and some treated unplanned admissions separately from planned readmissions.

Different types of feature reduction methods were employed across literature. However, they can be broadly categorized into two main approaches: information based reduction and dimension reduction. For example, one model used the LACE technique for feature selection which is information based (Arian Hosseinzadeh et al.,2013). LACE is defined by the following factors: length of stay (L); acuity of the admission (A);

comorbidity of the patient (C) (measured with the Charlson comorbidity index score); and emergency department use (E) (measured as the number of visits in the six months before admission). Gini indexing is a type of information based feature reduction technique which is a standard measure of statistical dispersion with the value between zero and one. Gini index is commonly used in the field of Economics as a measure of inequality of income (Arian Hosseinzadeh et al.,2013). Some models employed the automatic feature reduction methods available with some standard machine learning algorithms. Most of them have an algorithm-specific feature reduction ability. These algorithms automatically generate features with greatest predictive ability to the outcome label and eliminate those features that are noisy and non predictive of the outcome class. To reduce dimensionality, some models used PCA analysis whereas some others used frequency-based feature selection techniques i.e. selecting the features that are most common and correlated, and eliminating them (Arian Hosseinzadeh et al., 2013). A few models used the technique of oversampling method. This method seeks to change the distribution of training data in a way that both outcome classes are well represented. It resamples the rare class records so that the resulting training set has an equal number of records for each (Vivek R Rao et al., 2014). This approach had a positive effect on the accuracy of models.

3.2 Risk Models

Risk models mentioned in the literature were varied. A detailed review of the models is available in (Kansagara, D., Englander, H., Salanitro, A., Kagen, D., Theobald, C., Freeman, M., & Kripalani, S. 2011). The most commonly used method for prediction in the literature has been logistic regression and its several variants, such as Penalized Logistic regression with L1 and L2 based regularization. Random Forests, Support Vector Machine and most recently Deep Learning techniques (Futoma et al., 2015). Logistic Regression (LR) is an optimization problem that involves the identification of vector coefficients based on input vectors and outcome class. Penalized LR involves adding a regularization parameter to the loss function. Ridge regression and Lasso Regression are used widely. Some of them tried to generalize models to global from local cohorts. The best choice of model depends on the study and most of them selected a model that works for their requirements which makes it difficult to compare among the models. Generalizability of these models is very challenging because of the diverse set of complex factors involved and accuracy is poor in general. Some of the models in this literature review were targeted to calculate the readmission risk scores of patients, some were targeted to find patients who are at high risk so that appropriate care can be taken for those patients and almost all of the models have an overall poor predictive scores and accuracy can be improved considerably (Kansagara D, Englander H, Salanitro A, et al. 2011). All the models examined were based on supervised learning classification algorithms. Starting from simple logistic regression to general classifiers like Naive Bayes classifier (Arian Hosseinzadeh et al., 2013) to discriminative classifiers such as decision tree classifier were used. Random Forest classifiers were used in majority of these models even though it is computationally expensive compared to other models and scaling a random forest algorithm is very challenging. Random Forests are an ensemble learning method, where a large number of binary classifiers are trained separately and then combined to a single unified prediction. In random forests case, each classifier is a decision tree and decision tree is a predictive model which maps features data to a class using a tree structure. Some tested a support vector machine approach (SVM) whose goal is to maximize the margins between features and hyperplane used to separate two classes. Both linear (uses linear kernel) and nonlinear (uses polynomial kernel) SVM models were examined. Some models exploited the big data solutions like Hadoop (Rao, V. R., Zolfaghar, K., Hazel, D. K., Mandava, V., Roy, S. B., & Teredesai, A. 2012) and Mahout to accomplish speed when they were dealing with millions of patients records. Regardless of the model used, one of the biggest challenges facing all recommender systems is the sparse data problem. In a system with many patients and many features, each patient will only have a fraction of the features present in the data which is a common problem among hospital data.

3.3 Evaluation

The ideal readmission predictor is one that predicts an accurate risk probability for each hospitalization. Classic machine learning model evaluation metrics such as precision, recall, accuracy, Area Under the Curve (AUC), sensitivity, specificity, F-measure and receiver operating characteristics are used to evaluate risk prediction systems. The following section will cover the details of different evaluation metrics that are being used in risk prediction system.

The available data that is used for model is typically divided into sets of training data and test data. Researchers set aside a small part of the real data (typically 10-20%)

set as test data because it is not feasible to test the system using new hospitalizations without deploying the system. The preferences of test data are not present in the training data that is used in machine learning models so that test data can be used independently for evaluation. The risk prediction system predicts readmissions in the test data and the readmissions labels estimated are compared to the actual values to calculate different metrics. For readmission predictions, precision can be defined as the proportion of test instances classified as readmissions that actually belong to readmissions class. Recall can be defined as the proportion of total test instances that were identified by classifier as belonging to readmissions class. Mathematically, precision with respect to readmission is

true positives / (true positives + false positives)

where true positives are test instances where the model has accurately predicted as readmissions and false positives are test instances where the model has incorrectly predicted as belonging to readmissions class. Recall can be defined as true positives / (true positives + false positives), where false negatives are test instances the classifier has wrongly predicted as not belonging to readmissions class. F1 score is the harmonic mean between precision and recall

*F1 = 2 * (Precision * Recall) / Precision + Recall*

The precision is important if there is a high cost related to falsely predicting patients to belong to the class Readmission. Recall is relevant if the detection of patients that belong to Readmission is the main goal. The accuracy is the traditional evaluation measure that gives a global insight in the performance of the model. Some researchers used sensitivity, specificity, F-measure and receiver operating characteristics. A Receiver Operator Characteristic (ROC) curve shows hit/miss rates for different classification thresholds (framework). The area under an ROC curve is a performance measure with perfect success having area 1 and a random success having area 0.5. These curves are very similar to precision/recall curves; recall corresponds with sensitivity (hit rate) and precision corresponds with specificity with miss rate plotted on x-axis and hit rate is plotted on y-axis. The AUC measure is typically interesting when the problem is imbalanced when labeled dataset is highly skewed that is when the number of instances with No Readmission label significantly outnumbers the number of instances with class label Readmission (Vivek R Rao et al., 2014). Most models have poor predictive performance. Among models that used 30 days readmission as the outcome, most of them had AUC < 0.70 (refer: systematic review) with few exceptions which used small samples (700 training samples). One way to split the data into test and training data is to randomly assign instances to training and test set but this might not give the complete picture of performance because the data can be split in number of different ways. k-fold cross validation addresses this issue by randomly splitting the original data into k-folds, and k-1 of these folds are used for training, while the left out fold used for testing. These steps are repeated to use each fold as the test set while training on the other folds that are remaining. The final reported metrics are then averaged across the k-folds to compute models average performance. k varied from 3 to 10 in the literature of readmission prediction. k-fold cross validation gives more realistic picture of model performance since it is trained and tested on different datasets several times. Most of the models exploited the cross validation techniques (majority used 3-10 folds) to improve the accuracy of the model.

4. **Methods**

4.1 Data Collection

First, to gather data for this study, patient cohorts for three specific conditions: heart failure (HF), chronic obstructive pulmonary disease (COPD), and Diabetes (DIAB) were identified and the study data was prepared. Patient data was gathered from the UNC Health Care System to support this study. Data for patients from the UNC Health Care system were retrieved from the Carolina Data Warehouse for Health (CDW-H). All patients are adults (>17 years) who have both inpatient and outpatient medical data in the CDW-H since 2008. All patients had at least one hospitalization for the specific cohort condition. With IRB approval, operational data for patients admitted to UNC Hospitals between January 2008 and August 2015 were obtained. UNC health care system started using EPIC health care systems from 2014-April. The data gathered included data from EPIC system as well as old system. The six and half year sample included a total of 20293 patients with 59794 variables (12 main classes: BLOOD BANK, CPT, CPT4, ENCOUNTER, ICD9, ICD9-CM, LAB (lab code system used by EPIC health care system), LAB-LEGACY (lab code system used by LEGACY system), Medications, Microbiology, NDC, Pathology and Cytology). More relevant for this study, ICD9, ICD9-CM, CPT, CPT4 and Medications were used for while constructing models. Integrating data from LEGACY and EPIC systems was challenging because of the complex structure of data and interoperability issues. Data from EPIC systems were considered for this study. Readmit distributions and events distributions were analyzed to come up with filter criteria. Generalized data models were created to convert the diverse set of patient information provided by health care system into input that is suitable for machine learning risk models and exploratory analysis. The main idea is to have a general database models to capture patient history as events with timestamps which makes it easy to apply filter criteria and extract features for machine learning models. Patients information is either static (gender, demographic information) or temporally varying (emergency visits, lab tests) and the general model incorporates temporal data as a sequence of events using timestamps associated with them. This type of general framework for automated feature extraction and risk prediction was used in (framework piece) and provided useful for scaling up and generalizing the model across different DRGs (Diagnostic related groups). Data received from health care was stored in mysql database using the common data model for further analysis. Events data from the database was further analyzed to come up with inclusion/exclusion criteria for the dataset for risk models. Table 1 describes number of events in recorded monthly from EPIC healthcare System. There is a sudden increase in events recorded from April 2014 because the roll out of EPIC system was transitioned completely by that time. Table 2 describes the month wise distribution readmissions and the December 2014 has very few readmission because of lack of data of admissions from January 2015. Data from April 2014 to November 2014 (8 months) was considered for this study.

Table 1: Monthly distribution of events recorded

Month	*Number of events*
01/01/2014	792
01/02/2014	1922
01/03/2014	2370
01/04/2014	145746
01/05/2014	161007
01/06/2014	183601
01/07/2014	218404
01/08/2014	230690
01/09/2014	227393
01/10/2014	235979
01/11/2014	214314
01/12/2014	228719
01/01/2015	230
01/02/2015	263

Table 2: Readmit analysis monthly

Month	*Readmissions*	*Hospitalizations*
April	305	1674
May	360	1813
June	383	1914
July	431	2105
August	404	2078
Sept	418	2145
Oct	402	2184
Nov	382	2066
Dec	159	2236
Total	**3244**	**18215**

Table 3: Descriptive statistics for the three cohorts

Condition	*Total hospitalizations*	*Readmission hospitalizations*	*Readmission rate*	*Unique Patients*
COPD	6542	1151	0.18	5695
HF	4890	1028	0.21	3929
DIAB	7033	1242	0.18	6236

After data filtering, smaller and more focused disease-specific cohorts for further analysis was defined. Using the appearance of the ICD-9 codes during a hospitalization as inclusion criteria, three groups of hospitalizations corresponding to HF, COPD, and DIAB were defined. These cohorts ranged in size from X to Y hospitalizations (for PN and HF, respectively). Because some patients were hospitalized more than once, the number of unique patients represented is slightly smaller as shown in the detailed descriptive statistics reported in Table 3. Each of the hospitalizations in the three cohorts was classified with one of two labels: (1) resulting in readmission (2) not resulting in readmission. The label for a given hospitalization was determined by looking within the same patient's data for a subsequent admission to the hospital within 30 days of the discharge date (regardless of reason for the subsequent hospitalization). After applying this classification logic to all three cohorts, readmission rates ranged approximately from 16% to 19% across the conditions.

4.2 Feature Description

The fundamental goal of this study was to characterize the change in readmission risk over time by creating Machine Learning models using data from different time frames. Toward this goal, first a binary outcome vector for each condition [COPD, HF, DIAB] was defined. The length of each outcome vector reflected the number of hospitalizations for the corresponding condition. Each value in the vector was either one or zero, with a one for each hospitalization labeled as a readmission and zero for all others. After that, for each visit, feature vectors generated from ICD9codes, CPT and Medications codes. The value was set to 1 if any of the codes exist for that visit, otherwise the value was set to 0. This consists of 41349 binary variables coding the ICD9 (10631), medications (18745), CPT (4093) and CPT4(7990) codes. Unfortunately, the demographic data (age, sex and race) was not provided so it was not considered for this analysis. This data was then converted to two dimensional array of size (n_samples, n_features) for python's Scikit-Learn analysis.

4.3 Models

Readmission risk prediction is treated as a binary classification problem for this study. Classification algorithms takes labeled data as input (training data) and predicts unseen data (test set) labels. The learning function of algorithm will first fit to the training data and then try to predict the labels for test set. In Scikit-Learn, these two steps needed to be provided explicitly for the algorithm. Logistic Regression algorithm was used to construct models as it was used in many of models constructed in literature (systematic review piece). Logistic regression outputs a predicted label based on the probability of the test instance belonging to a certain label and the label with highest probability was used for predicted label.

For each condition (COPD, HF, DIAB), models were generated by using patient data from four time intervals namely 15 days, 30 days, 45 days and 60 days prior to hospital admission. These models were compared to the baseline model generated from data during hospitalization. Feature engineering techniques provide by Scikit-Learn were used for model creation. Feature engineering is the process of transforming raw data into features that better represent the underlying problem to the predictive models, resulting in improved model accuracy on unseen data (refer 5). Less features can lead to less overfitting and generalize better and normally provide higher accuracy (refer 5). Univariate feature selection methods were used for reducing the feature set. Univariate feature selection works by selecting the best features based on univariate statistical tests. Select Percentile feature reduction method was used which removes all but top 10 percent highest scoring percentage of features. In order to fairly compare models, Stratified K Fold Cross validation with 10 folds was used. It was used because the training data is unbalanced with “not readmission” outcome label appearing majority of times (greater than 80%). Stratification makes sure that the percentage of samples for each class is similar across folds which ensures that there is no bias in any folds to have only 1 particular class dominating the other one.

4.4 Algorithms

In this study, a generalized algorithm for hospital readmission is developed. The algorithm can be used for future applications with different settings as well. There are two main steps involved in the algorithm.

Step 1: Data generation

- Identify COPD, HF and DIAB patient cohorts using ICD9 codes
- For each condition, label each hospitalization as either readmit or not readmit based on 30-day readmission time interval
- For each hospitalization, get all the codes (ICD9, Medications and other codes) present based on time prior to admission as a filtering criteria. Time varied from 0, 15, 30, 45 and 60 days in this study

- Initialize a matrix with number of hospitalizations as rows and features as columns. Initialize all the values to be zero. For each hospitalization, if a feature appears in the hospitalization data then set the value in the matrix to 1. Also append a new column for outcome label and set the corresponding outcome label which was already calculated above
- Generate a csv file from the matrix created above.

Step 2: Binary Classification

- Load data from the csv file generated above and load it as a matrix that is suitable for the machine learning model. (Scikit learn is used for this study)
- Separate the outcome labels and drop the column from the matrix to avoid using the label as input to machine learning algorithm
- Apply feature engineering on input data. This study used selectKPercentile method using k as 10 which reduces the features to top 10 percentile features that are most predictive based on f_classifcation univariate measure.
- Train the logistic regression model by using the new features and the label. Use stratified K folding as the data is unbalanced
- Get the metrics for evaluating the model performance.

The above algorithm was implemented in python using pandas and scikit learn libraries. Code is available at https://github.com/sreenug/readmission and is publicly accessible.

5. **Results**

Results for each of the conditions are shown in Table 4 (COPD), Table 5 (HF) and Table 6 (DIAB). Best results for each condition are highlighted in bold for reference.

Usually, classification results are compared with a baseline random model which assumes 50% random chance of identifying an instance belonging to the correct class. That is, if a classifier just randomly guesses labels (0 and 1 in this case) to instances, it is assumed that the model predicts 50% of labels correctly. However, the baseline random model assumes that the labels in training and test sets are evenly balanced with one half of instances consisting of readmission labels and the other half consisting of "no readmit" labels. This assumption will not hold true in the hospital readmission case since the labels are not uniformly distributed due to low readmission rates. This class imbalance problem (Chawla, 2010) is a common issue in the healthcare field as only a small percentage of population are afflicted by diseases and illnesses.

The most common evaluation metric in literature for predicting early readmission, area under the ROC (AUC) was used. It is reported in Tables 4, 5, 6 along with accuracy, precision and F-measures with respect to the readmission class. Among all three cohorts, baseline models that considered data from hospitalization and without any patient history consistently outperformed all the other models which considered patient history when comparing with the metric of accuracy. This is verified in Fig 2. In comparison with the AUC metric, HF and DIAB models, which took past 45 days data into consideration, outperformed all other models. This is verified in Fig 1. Of particular interest is the low HF model accuracy when compared to COPD and DIAB models, despite HF cohort having the highest readmission rate and its data is far more balanced than the other cohorts. The results also show that COPD with the highest accuracy is most predictive among the three cohorts, as shown in Fig. 1

Table 4: COPD results from 10-fold cross validation

Time prior to admission	*Sample Size*	*Readmission Rate*	*AUC*	*Accuracy*	*Precision*	*F-Measure*
0	6542	0.18	0.58	**82.86**	0.51	0.29
15	6542	0.18	**0.59**	82.62	0.51	0.31
30	6542	0.18	**0.59**	81.55	0.45	0.31
45	6542	0.18	0.58	80.79	0.42	0.31
60	6542	0.18	0.57	79.26	0.35	0.27

Table 5: HF results from 10-fold cross validation

Time prior to admission	*Sample Size*	*Readmission Rate*	*AUC*	*Accuracy*	*Precision*	*F-Measure*
0	4890	0.21	0.56	**79.68**	0.51	0.28
15	4890	0.21	0.57	78.45	0.45	0.28
30	4890	0.21	0.57	77.57	0.42	0.32
45	4890	0.21	**0.58**	77.91	0.43	0.32

60	4890	0.21	0.57	76.95	0.40	0.29

Table 6: DIAB results from 10-fold cross validation

Time prior to admission	*Sample Size*	*Readmission Rate*	*AUC*	*Accuracy*	*Precision*	*F-Measure*
0	7033	0.18	0.55	**81.27**	0.49	0.21
15	7033	0.18	0.55	81.23	0.49	0.21
30	7033	0.18	0.56	80.14	0.42	0.25
45	7033	0.18	**0.57**	79.52	0.40	0.27
60	7033	0.18	0.55	78.9	0.37	0.25

Fig 1: AUC Comparison among patient cohorts

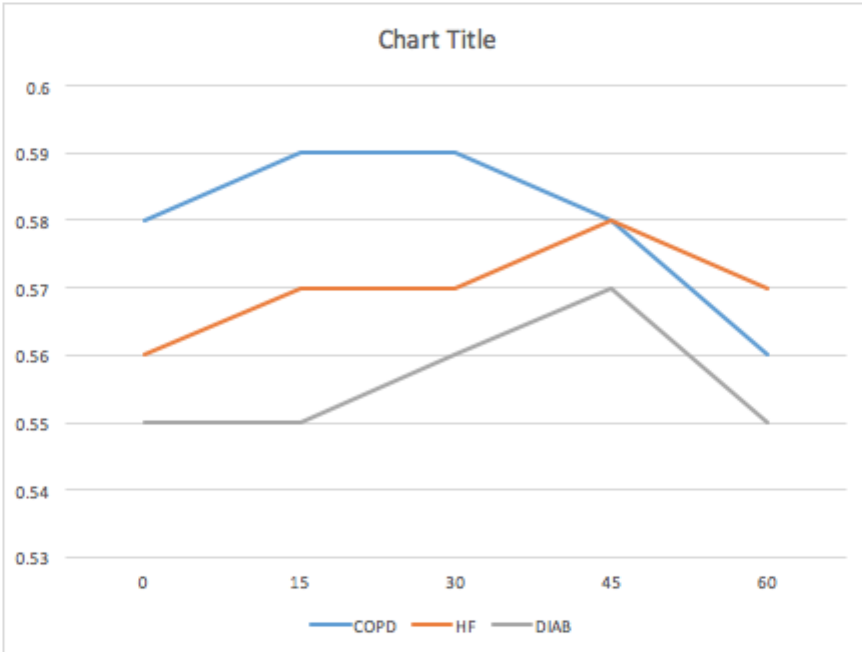
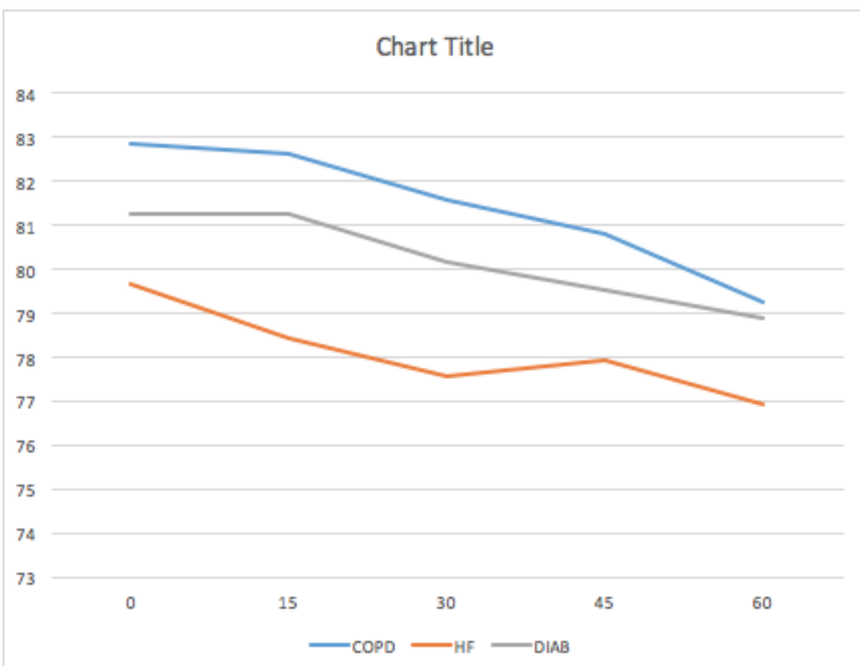


Fig 2: Accuracy comparison among patient cohorts



6. Discussion and Conclusion

Leveraging the Electronic Health Records (EHR) to construct features and labels, this study developed and tested a Logistic Regression algorithm to predict and the risk of readmission by considering patient's' history. For each condition, comparing the baseline model to other models considering patient's history, it is found that the latter did not produce better predictive performance than the baseline model. This might be because of increase in number of features used. Models that considered history have more features for prediction, and adding on more number of features could lead to over fitting and a noisy data set. To avoid these problems, more complex feature representation can be used and the model can be retrained with new data contents or newly added attributes. Using different feature representation for history and a different feature representation for baseline model can be explored to build a more robust model. It is also possible to test the features generated from more complicated feature engineering on different machine learning algorithms to improve the results. Instead of just considering 60 days of history, longer periods could be considered for further analysis. There are several important limitations that should be taken into consideration before generalizing the results obtained from this study. The size of dataset considered is small. Only 6 months' data has been used for prediction along with varying 60 days of past data. In this study, models were created using only ICD-9 codes and medications without using demographic information. Repeated observations of codes were not considered for feature creation since only binary feature representation was used. Counting the occurrences of different codes and doing frequency analysis might also improve the results. It is also likely that the reliability of ICD-9 codes and medication data might have been impacted by recording errors or misdiagnoses. However, the results might change if more data especially of greater duration is considered for prediction. The current fast pace of research in Machine Learning will improve the model fitting to increase its prediction precision, which might produce different results for this study.

Bibliography

Jencks, S. F., Williams, M. V., & Coleman, E. A. (2009). Rehospitalizations among patients in the Medicare fee-for-service program. New England Journal of Medicine, 360(14), 1418-1428.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., ... & Duchesnay, E. (2011). Scikit-learn: Machine learning in Python. The Journal of Machine Learning Research, 12, 2825-2830.

Balaban, R. B., Weissman, J. S., Samuel, P. A., & Woolhandler, S. (2008). Redefining and redesigning hospital discharge to enhance patient care: a randomized controlled study. Journal of general internal medicine, 23(8), 1228-1233.

Xu, Y., Hong, K., Tsujii, J., Eric, I., & Chang, C. (2012). Feature engineering combined with machine learning and rule-based methods for structured information extraction from narrative clinical discharge summaries. Journal of the American Medical Informatics Association, 19(5), 824-832.

Liaw, A., & Wiener, M. (2002). Classification and regression by randomForest. R news, 2(3), 18-22.

Zolfaghar, K., Meadem, N., Teredesai, A., Roy, S. B., Chin, S. C., & Muckian, B. (2013, October). Big data solutions for predicting risk-of-readmission for congestive heart failure patients. In Big Data, 2013 IEEE International Conference on (pp. 64-71). IEEE.

Rao, V. R., Zolfaghar, K., Hazel, D. K., Mandava, V., Roy, S. B., & Teredesai, A. Readmissions Score as a Service (RaaS).

Hosseinzadeh, A., Izadi, M. T., Verma, A., Precup, D., & Buckeridge, D. L. (2013, June). Assessing the Predictability of Hospital Readmission Using Machine Learning. In IAAI.

Kansagara, D., Englander, H., Salanitro, A., Kagen, D., Theobald, C., Freeman, M., & Kripalani, S. (2011). Risk prediction models for hospital readmission: a systematic review. Jama, 306(15), 1688-1698.

Perotte, A., Ranganath, R., Hirsch, J. S., Blei, D., & Elhadad, N. (2015). Risk prediction for chronic kidney disease progression using heterogeneous electronic health record data and time series analysis. Journal of the American Medical Informatics Association, ocv024.

Sculley, D., Holt, G., Golovin, D., Davydov, E., Phillips, T., Ebner, D., ... & Young, M. (2014). Machine learning: The high interest credit card of technical debt. In SE4ML: Software Engineering for Machine Learning (NIPS 2014 Workshop).

Shams, I., Ajorlou, S., & Yang, K. (2014). A predictive analytics approach to reducing 30-day avoidable readmissions among patients with heart failure, acute myocardial infarction, pneumonia, or COPD. Health care management science, 18(1), 19-34.

Futoma, J., Morris, J., & Lucas, J. (2015). A comparison of models for predicting early hospital readmissions. Journal of biomedical informatics, 56, 229-238.

He, D., Mathews, S. C., Kalloo, A. N., & Hutfless, S. (2014). Mining high-dimensional administrative claims data to predict early hospital readmissions. Journal of the American Medical Informatics Association, 21(2), 272-279.

Ian H. Witten, Eibe Frank , Mark A. Hall (2011). Data Mining: Practical Machine Learning Tools and Techniques

Hoens, T. R., & Chawla, N. V. (2010). Generating diverse ensembles to counter the problem of class imbalance. In Advances in Knowledge Discovery and Data Mining (pp. 488-499). Springer Berlin Heidelberg.

Tran, T., Luo, W., Phung, D., Gupta, S., Rana, S., Kennedy, R. L., ... & Venkatesh, S. (2014). A framework for feature extraction from hospital medical data with applications in risk prediction. BMC bioinformatics, 15(1), 425.