Precise Prediction for Managing Chronic Disease Readmissions

Sankalp Khanna, Justin Boyle, Norm Good

Abstract— **Potentially preventable hospital readmissions have a crippling effect on the health of chronic disease patients and on healthcare funding and resource utilization. While several prediction models have been proposed to help identify and manage high risk patients, most offer only moderate predictive power and discriminative ability. We develop and validate several models that utilize cohort population and clinical data and are capable of precisely identifying chronic disease patients with a high risk of rehospitalization within 30 days. Cross validation and receiver operating characteristic curve analysis are used to examine the predictive power of the models. The developed models offer high precision and discrimination and outperform current state of the art models. Delivering between 73% and 79% sensitivity at 93% specificity, the models offer excellent candidate prediction algorithms for the battle against the burden of chronic disease on the public health system.**

I. Introduction

Unplanned hospital readmissions, especially in chronic disease patients, are credited with being responsible for a significant portion of health spending in most countries around the world [1-2]. With statistics suggesting that 90% of 30-day rehospitalizations are unplanned, and that 20%-50% of these are preventable [3], reducing potentially preventable readmissions is well regarded as an efficient strategy for reducing cost and hospital workload, and importantly, improving the quality of patient care. Recent efforts to measure readmission rates and penalize hospitals based on these [4-5] have further motivated hospital services to identify patients at high risk of readmission early during their admission to enable planning of appropriate interventions as part of the discharge planning process.

Several models have been proposed over recent years for predicting the risk of hospital readmission [6-12]. A recent comprehensive survey of these risk prediction models [12] found that while useful, most current models performed poorly and greater efforts were needed to improve their efficacy. More specifically, current models were found to have poor or moderate predictive and discriminative ability. Further, while several intervention programs have been proposed to help reduce unplanned readmissions, it has been shown that no single intervention implemented alone contributes significantly to reductions in 30-day readmission rates [13]. The impact of these interventions will no doubt be improved if a robust model offering high predictive power is available for selecting candidates for referral to the program. Our study is aimed towards filling this void.

With high precision and discriminative ability as primary objectives, we use administrative and clinical information for patients belonging to a lower socio-economic region of Queensland, Australia, to develop and validate prediction models for identifying chronic disease patients with a high risk of readmission within 30 days of discharge from hospital. We independently validate our models and compare the performance with the LACE index, proposed by van Walraven et al [7]. We also discuss the proposed integration of these models into a hospital trial, generating daily lists of high-risk patients to proactively inform and support discharge planning and community interventions aimed at reducing potentially preventable readmissions of chronic disease patients.

II. Methods

Inpatient admission and emergency presentation data from 2005-2010 for patients residing in a lower socio-economic area of Queensland, Australia, was obtained from all 4 public hospitals within the catchment health district. Ethics approval for this research was obtained from the Queensland Health Metro South Health Services District. Microsoft Excel 2007 and Matlab 7.13.0 were employed for data manipulation and statistical analysis.

TABLE I. List Of ICD-10 Diagnosis Codes Used To Identify Chronic Disease Patients for the Study

Diagnosis Code Block	Description
E11*	Type 2 Diabetes Mellitus
I25*	Chronic Ischaemic Heart Disease
I50*	Heart Failure
I60*	Subarachnoid Haemorhage
I61*	Intracerebral Haemorrhage
I62*	Other Nontraumatic Intracranial Haemorrhae
I63*	Cereral Infarction
I64*	Stroke, Not Specified as Haemorrhage or Infarction
J44*	Other Chronic Obstructive Pulmonary Disease
J45*	Asthma
J46*	Status Asthmaticus
N18*	Chronic Kidney Failure
Z49*	Care Involving Dialysis

The collected data was cleaned by removal of incomplete/inconsistent records. The study focused on the patient cohort that had at least one chronic disease admission (identified by ICD-10 diagnosis codes, see Table I) during the analysis period. A large proportion of admissions consisted of planned dialysis. To reduce the potential bias caused by these, patients with only planned dialysis were removed from the cohort. All inpatient admissions (including dialysis admissions, if any) were included for the remaining patients in the cohort. The resulting dataset comprised 67302

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encounters representing admissions between 2005 and 2009 which were used to build the model, and 14456 encounters representing admissions in 2010 which were used for independent validation.

TABLE II. VARIABLES AVAILABLE AS PREDICTORS

Visit Number	Top Ten ICD Code - E11	Account (Billing) Class
Length of Stay	Top Ten ICD Code - I10	ICD Code 1
Previous Length of Stay	Top Ten ICD Code - I25	ICD Code 2
Chronic Disease Admission ?	Top Ten ICD Code - Z86	Number of ICDs
Age	Top Ten ICD Code - Y92	Charlson Comorbidity Index
Sex	Top Ten ICD Code - E78	Number of Interventions
Marital Status	Top Ten ICD Code - N18	ED Visits - Last 30 Days
Admit Unit	Top Ten ICD Code - J44	ED Visits - Last 60 Days
Country of Birth	Top Ten ICD Code - I50	ED Visits - Last 90 Days
Planned Same Day Admission?	Top Ten ICD Code - Z72	ED Visits - Last 120 Days
Insurance Status	Ethnic Status	ED Visits - Last 365 Days
Admit Type (Elective/Emergent)	Return Time (from Previous visit)	Disease Related Group (DRG)
Medicare Status		

Table II presents the list of predictors that were used for the analysis. The time taken for each encounter to result in a subsequent encounter (Time-to-Return) was recorded and used as a response variable for modeling and validation. As Time-to-Return exhibited a lognormal distribution, raw values were log-transformed prior to analysis. For Time-to-Return, 30 days was chosen as the benchmark for identifying unplanned readmission as it is well regarded as the optimal choice for the purpose [16-18], and is also employed by the metrics used for evaluating and comparing hospital performance [4-5].

A filtered training data set was created from the initial training sample by excluding index admissions (i.e. first admission) during the data collection period. Both unfiltered and filtered training datasets were employed for modeling to study if removal of index admissions (i.e. admissions with null values for variables dependant on previous visits like Return Time, Previous Length of Stay etc.) improved the prediction model, and whether the risk of readmission could be predicted for patients during their first visit based on available variables (e.g. Age, Sex, Marital Status, etc).

Stepwise multiple linear regression was used to identify significant subsets of variables on the filtered and unfiltered datasets. Significance value cutoffs of p=0.05 and 0.10 were employed as thresholds for inclusion and removal of variables from the stepwise model respectively. Robust regression and Ordinary Least Squares (OLS) regression were employed for building models on the significant subset of variables identified. Robust regression was chosen as it allows the model to better handle outliers, i.e. data points that deviate markedly from the rest of the data.

Each of the four developed models was validated on filtered (index admissions removed) and unfiltered versions of the evaluation dataset. Variable thresholding was undertaken during validation to convert the score to a binary value representing the prediction for whether the encounter would result in a return admission within 30 days. This was then compared to the observed (validation) value to verify if the prediction was successful or not. Sensitivity, specificity, accuracy and precision were calculated for each encounter and the Receiver Operator Characteristic (ROC) graph was generated for each evaluation. The c-statistic, representing the area under the ROC curve, was then calculated for each model as a measure of discrimination and used to compare the performance of the models. An optimal threshold, T1, was then chosen for model use and comparison, and sensitivity, specificity, precision and accuracy were calculated at threshold T1 for each model.

For comparison, the LACE index [7] was also used to predict the risk of readmission within 30 days on filtered and unfiltered versions of the evaluation dataset. The index was chosen because it could be readily applied to the variable set used in this study. Sensitivity, specificity, accuracy and precision were calculated at each index score and the ROC curve was plotted and analyzed to compare the performance of the LACE index with our models.

Correctly and incorrectly predicted encounters were also analyzed for a qualitative understanding of performance and discriminative ability of the index.

III. RESULTS

Stepwise selection revealed that filtering out the index admissions did not have any impact on the selection of significant variables. Both, the complete and the filtered training sets, returned the same 19 significant variables in the stepwise selection (see Table III).

TABLE III. SIGNIFICANT PREDICTORS RETURNED BY THE STEPWISE MULTIPLE LINEAR REGRESSION ALGORITHM

Visit Number	Top Ten ICD Code - E78
Length of Stay	Top Ten ICD Code - N18
Return Time (from Previous Visit)	Top Ten ICD Code - J44
Age	Top Ten ICD Code - Z72
Sex	Ethnic Status
Marital Status	Account (Billing) Class
Admit Unit	Charlson Comorbidity Index
Planned Same Day Admission?	Number of Interventions
Insurance Status	ED Visits - Last 120 Days
Top Ten ICD Code - Z86 ?	

Figure 1 presents the ROC curves for the performance of all four models on filtered and unfiltered validation datasets. It was observed that ROC curves nearly overlapped across all models, with robust regression models marginally outperforming OLS regression models. The performance of the models can broadly be divided into categories – models developed using robust regression, i.e. models m1, m2 and models developed using OLS regression, i.e. models m3, m4.

The overall performance of all models was high, with all models achieving over 90% area under the curve in the ROC analysis (see c-statistic, Table IV). Table IV also provides a comparison of sensitivity, specificity, accuracy and precision levels at the chosen threshold level T1 (i.e. 93% specificity). At this level, models developed using robust regression reported over 78% sensitivity, 84% accuracy, and over 94% precision. In contrast, models developed using OLS regression reported 73% sensitivity, 81% accuracy, and 94% precision. No significant improvement was found in models that used the filtered training dataset.

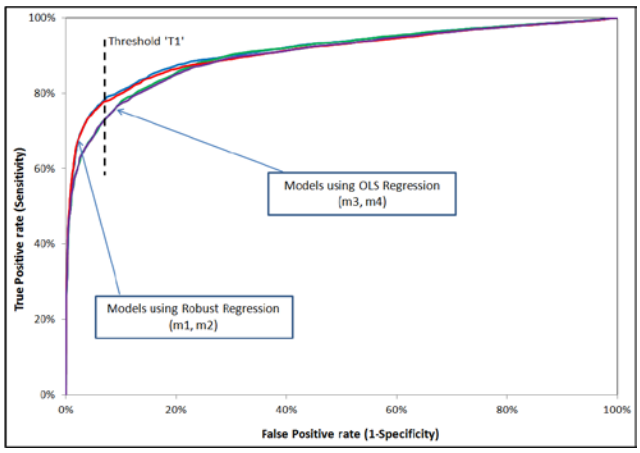

Figure 1. Receiver Operator Characteristic Curve for Developed Models

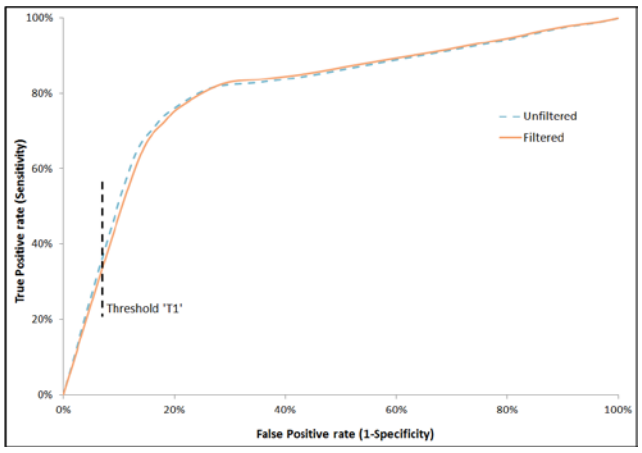

Figure 2. Inverted Receiver Operator Characteristic Curve for LACE Index [7]

In comparison, the LACE index [7] applied to our data resulted in lower performance for predicting the risk of readmission within 30 days. Validation over the filtered dataset returned only marginal improvement as compared to the unfiltered dataset. In both cases however, the area under the ROC curve for the LACE index was under 20%, and sensitivity over 50% could only be achieved at the cost of under 9% specificity and 48% positive predictive power. Inverting the ROC curve (see Figure 2) returned 80% area under the curve with 81% sensitivity at 73% specificity and 82% precision for unfiltered data and 82% sensitivity at 71% specificity and 83% precision for filtered data respectively.

Analysis showed that most of the significant variables were common to those reported by other algorithms. Analysis of the correctly and incorrectly predicted encounters revealed that several Chronic Disease patients also had Dialysis admissions during the reference period. The main outcome measure (30 day readmissions) was accurately predicted for patients within this group.

IV. Discussion

The key contribution of this study is the development and validation of precise predictive models for identifying chronic disease patients with a high-risk of 30 day rehospitalization. It is intended that the chosen model will be used to identify patients while in hospital so appropriate interventions can be incorporated in their discharge planning.

Employing a mix of administrative and clinical data, the predictors represent a good mix of parameters that can be easily accessed from existing information systems without requiring additional input from clinical staff. This overcomes ad-hoc approaches employed by some intervention models and equips clinical staff with a consistent and reliable mechanism for risk stratification.

The ROC analysis reveals that the performance of the models is not affected by some missing predictors in the evaluated admission. Interestingly, one of these predictors, Return Time, representing the time between the previous and current hospital admission episodes, was still selected as a significant variable in the stepwise fit.

The prediction models proposed herein significantly outperform the LACE index. And while van Walraven et. al. have stated that the LACE index was specifically designed for the test population on which it was evaluated and may not have general applicability, the performance of our models exceeds the performance of the index as reported in the original study. It would however be interesting to evaluate the performance of the LACE score as a predictor in future models.

The performance of our risk prediction models is also higher than that reported by validation studies on PARR [6] and other models reviewed by Kansagara et. al. [12]. Achieving up to 79% sensitivity at 93% specificity, our prediction models are suitable candidates for identifying high-risk patients for community interventions as planned. Further, offering a very low false positive rate with up to 95% precision, the models are well suited for use where budget constraints require precise prediction to ensure resources are targeted to patients that need them the most. Use of the filtered training data delivered identical performance to the complete dataset, delivering a limited set of variables that could be used with ease for risk stratification algorithms.

V. Conclusion

We have developed and validated prediction models for identifying chronic disease patients that are at high risk of rehospitalisation within 30 days of discharge. The developed models exhibit high sensitivity at high specificity levels, and higher predictive power and discrimination ability compared to current state of the art prediction models. These characteristics can help target interventions towards where they are most needed and help prevent avoidable readmissions to hospitals.

We are currently working towards initiating a trial of the models to identify candidates for a discharge planning and community intervention program targeted at reducing potentially preventable readmissions for chronic disease patients. We are also working towards incorporating information from outpatient, pharmacy, and community

TABLE IV. PERFORMANCE OF PREDICTION MODELS AT THRESHOLD T1 (I.E. 93% SPECIFICITY).

Model	Training Dataset	Validation Dataset	Sensitivity	Specificity	Accuracy	Precision	c-statistic
m1*	Unfiltered	Unfiltered	78%	93%	84%	94%	0.909
		Filtered	78%	93%	84%	94%	0.909
m2*	Filtered	Unfiltered	79%	93%	84%	95%	0.914
		Filtered	79%	93%	84%	95%	0.914
m3#	Unfiltered	Unfiltered	73%	93%	81%	94%	0.902
		Filtered	73%	93%	81%	94%	0.902
m4#	Filtered	Unfiltered	73%	93%	81%	94%	0.906
		Filtered	73%	93%	81%	94%	0.906

Notes : * Denotes models employing robust regression, # Denotes models employing OLS regression.

health information systems, and exploring more complex models to further improve predictive power.

VI. LIMITATIONS

Data was collected from all hospital services within a selected catchment area, and the study focused on patients primarily belonging to a specified lower socio-economic region in the state. Further analysis needs to be undertaken before the models developed as part of this study can be applied outside this region. Also, the study was unable to account for patients that may have visited hospitals outside the catchment (e.g. interstate or overseas), or not returned because they died. Because of the planned use for the risk stratification algorithms, the model does not account for clinical and non-clinical indicators during the current visit when the model will be applied. The aim of preventing unplanned readmissions would benefit from research into how these indicators could be integrated into the process.

We also stress that the models were derived from historic patient records which included dialysis episodes (we however did exclude patients with treatment comprising exclusively of planned dialysis). Such episodes may be considered obvious in care planning, and care should be taken in comparing the performance of prediction algorithms that include this patient cohort.

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