# Multi-task Cox Proportional Hazard Model for Predicting Risk of Unplanned Hospital Readmission

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***Abstract* - Unplanned hospital readmissions are a tremendous challenge faced by medical providers in the United States: In 2015, 17.8% of Medicare and Medicaid patients returned to the hospital within 30 days of discharge. An unplanned readmission marks a setback in a patient's recovery and burdens hospitals financially--the estimated national cost of caring for readmitted patients is $15 billion annually. Financial penalties from the Center for Medicare & Medicaid Services intensify these costs, penalizing hospitals with high rates relative to the national average. At the University of Virginia Medical Center, the Medicare & Medicaid risk-adjusted readmission rate of 16.8% is higher than the national average of 15.2%. This higher than average rate leads to penalties, which are estimated at $764,000 for the 2017 fiscal year. The UVA Medical Center prioritizes reducing their readmission rate and has invested time and resources towards modeling readmission risks for their patients. Our research aims to improve the accuracy of risk projections at the Medical Center by exploring alternatives to current models. We developed a Cox proportional hazard model that takes in a set of covariates as input and predicts a patient's risk of readmission. The model had a concordance index of 0.70 resulting from 10-fold cross validation after applying the model to a test set. The Cox proportional hazard model was expanded using multi-task learning, a novel approach for survival analysis that is commonly used in classification. The new multi-task Cox proportional hazard model resulted in a concordance index of 0.52. Accurately predicting a patient's readmission risk will assist the UVA Medical Center in targeting high-risk patients during outpatient and follow-up care. Medical providers will be able to utilize the modeling output to better understand factors that influence the risk of readmission.**

*Index Terms* - Multi-task Cox Proportional Hazard Model, 30 Day Hospital Readmission Prediction, risk analysis, healthcare systems, machine learning

## Introduction and Motivation

A medical readmission is defined as an urgent medical situation requiring hospitalization within 30 days of discharge from a previous admission. While a number of reasons can lead a patient to an unplanned readmission, all readmissions tend to negatively affect patients and their recovery processes. Overall, a patient's health in the 30-day window reflects the quality of care administered by the hospital, as well as the hospital's ability to transition the patient to a follow-up care setting.

Patients and health insurance companies carry the financial burden of readmissions, paying an estimated $15 billion annually to hospitals to cover treatments during readmissions [1]. Government-funded insurance programs Medicare and Medicaid have the least ability to cover the costs of extraneous care, yet the nearly 18% of their patients facing a readmission in 2015 was highest among insurance providers [2]. As a result, in line with its efforts to improve the quality of care and curb hospitals' readmission rates, the Center for Medicare and Medicaid Services (CMS) began to enforce financial penalties on hospitals with high readmission rates, beginning in October 2012 [3].

CMS readmission penalties thus encourage hospitals to provide higher quality care and to continue interacting with patients throughout the 30 days following a hospitalization, to reduce the likelihood of readmissions. CMS penalties apply to readmissions for six specific conditions--acute myocardial infarction (heart attack), heart failure, chronic obstructive pulmonary disease (lung disease), hip and knee replacements, pneumonia, and stroke--with each condition having a unique penalty amount associated with it. CMS calculates a readmission payment adjustment for each hospital to measure their performance against the national average and penalizes hospitals as necessary [3].

The University of Virginia Medical Center's (UVAMC) current annual readmission rate is greater than the national average, at a 16.8% risk-adjusted rate compared to the national average of 15.2%, for data collected between July 2013 and June 2014 [4]. This rate covers only CMS patients--around 18,300 per year--accounting for 63.1% of UVAMC's total patient population [5]. While reducing their readmissions lowers CMS penalties, which is estimated at $764,000 for 2017, the real motivation lies in the desire to keep all patients healthy and out of the hospital [6].

The UVAMC's efforts through Locus Health, a local transitional care facility, prevented approximately 131 all-cause readmissions over an 11-month period in 2016 [5]. Locus Health determines their care intervention based off a Random Survival Forest (RSF) predictive model, developed by Dr. Robert Yerex of the UVAMC data analytics department. The RSF model creates an ordered list of Medicare and Medicaid patients within the 30-day discharge window, in order of their likelihood of readmittance on a given day. Patients are ranked relative to one another to show who has the highest risk [7].

As CMS continues to amend and add more diseases to their penalty program, the importance of accurately predicting when a patient may be readmitted becomes heightened. A more accurate model allows sharper predictions, but critical limitations exist in the current model used by the UVAMC. The current RSF model provides a list of patients ranked by their risk of readmission, but the differences in adjacent rankings are not equal and vary throughout the 30-day projected period. Thus, valuable information is lost through the ranking system.

These limitations guided our development of two new models to predict readmissions: the Cox proportional hazard model and the multi-task Cox proportional hazard model. The motivation for using these approaches stem from their lack of assumptions about the underlying hazard function, primarily focusing on how the predictors affect the hazard function. The multi-task Cox proportional hazard model works similarly Cox proportional hazard model, but it differs by training tasks simultaneously using a shared representation [8]. Our goal is to apply multi-task learning to the proportional hazard model to increase accuracy and predictive power of readmission projections.

## BACKGROUND AND LITERATURE REVIEW

### *I. Hospital Readmissions*

Research has been done to evaluate the existing CMS risk adjustment model used to calculate the financial penalties that hospitals receive. The existing model includes patients' age, sex, discharge diagnosis, and recent diagnoses as factors. These characteristics could potentially result in unfair penalizations since these factors are not distributed evenly across hospitals. A study published in the Journal of the American Medical Association assessed 29 patient characteristics as potential predictors of 30-day readmission when added to standard CMS risk adjustments of hospital readmission rates. Of the additional 29 patient characteristics assessed, 22 significantly predicted readmission beyond standard adjustments. Accounting for a comprehensive array of clinical and social characteristics substantially decreased the difference in patients' probability of readmission between hospitals with higher versus lower readmission rates. This finding suggests that CMS is penalizing hospitals to a large extent based on the population of patients they serve, not the quality of service provided by the hospital [9].

Efforts have also been put into directly developing models that predict 30-day hospital readmissions. A study published in Journal of Hospital Medicine proposed a risk prediction model incorporating Electronic Health Record (EHR) data from the "full" hospital stay. The study compared "full-stay" model performance to other risk prediction models such as a "first-day" model, which used a separately derived model using EHR data from the first day of hospitalization. Other models compared include two widely accepted and utilized models that rely on claims data-- the LACE model and the HOSPITAL model. Although the "full-stay" model had statistically better discrimination than other models, the improvement was modest. The "full-stay" model was able to predict a broader range of probabilities for readmission risk, but it was only slightly better in identifying the highest risk quintile compared to other models [10].

Numerous other studies have been conducted to develop predictive models that identify discharged patients at high risk of readmission. However, Kansagara et al. concluded that most readmission risk prediction models are limited in their ability to account for a holistic range of patient characteristics and to generalize to a broader and mixed population [11].

### *II. Survival Analysis in UVAMC Readmission Model*

Survival analysis is based on relating time before a "failure" event occurs to one or more covariates that may be associated with the length of that time. A survival model is based on a hazard function, which relates the risk of failure over time at baseline covariates to the parameters showing the effect of how the hazard function varies with changes to the covariates [12].

Dr. Robert Yerex, a senior data scientist at the University of Virginia Medical Center, developed a Random Survival Forest (RSF) model aimed at identifying patients at high risk of readmission. According to Dr. Yerex, the "predictors [are] identified primarily from CMS claims as found in the Claim and Claim Line Feed (CCLF) files provided by the CMS, in combination with location-based socioeconomic predictors to identify which patients are at high risk of 30-day readmission" [7]. In his model, the RSF technique produces predictions and highlights the most critical variables contributing to readmissions. Dr. Yerex also employs feature engineering, a process in which a large number of base dimensions are combined to create smaller features sets. By combining ICD-9 codes, the multi-digit International Classification of Diseases codes designating 14,000 specific conditions, he created new features within a patient's claim.

The RSF model utilizes a collection of decision trees, known as a random forest, during learning to derive a prediction for survival time given a particular set of covariates. The decision trees are built to classify an instance based on the values of its attributes. With readmissions, the splitting criterion used in growing a tree centers on survival time and censoring, with a censored observation meaning an instance which has incomplete information about a patient's outcome. These techniques of RSF are implemented in the randomForestSRC package in R, which Dr. Yerex used to model UVAMC 30-day readmission prediction.

Features in the final RSF model are of two forms; simple and engineered. Simple features are directly related to attributes in the dataset, such as age, gender, and race. Derived features are generated through complex combinations and transformations of attributes in the dataset. For example, a patient with the codes "572.3" and "249.10" would be combined into an engineered feature of "572.3:249.10" to show the progression of diagnoses. Our Cox and multi-task proportional hazard models utilize similar data transformations to group successive diagnoses of patients. Combining the simple and engineered features in his Random Survival Forests model, Dr. Robert Yerex's final model exhibited an average concordance index (CI) of 0.72 [7].

### *III. Cox Proportional Model*

A different survival analysis that is widely used is the Cox proportional hazard model. The Cox proportional hazard model is a semi-parametric model that is learned by optimizing a partial likelihood function. It assumes that the hazard function for different learning tasks are proportional over time; for example, that the hazard ratio between two patients is constant over the 30-day readmission window. The Cox model makes no assumptions about the underlying distribution of failure times, which would be the time a patient experiences a readmission. The log partial likelihood function of the Cox proportional model is shown in (1)

$$l(B) = \sum_{i=1}^{D} B^T s_i - d_i log[\sum_{j \in R_i} \exp(B^T z_j)] \tag{1}$$

where $D$ is the set of patients; $B_T$ is the transposed coefficient matrix; $s_i$ is the sum vectors $z_i$ over all individuals who "die" at time $t_i$; $d_i$ is the number of events at $t_i$ and $z_j$ is the covariate vector [13].

### *IV. Multi-Task Learning*

This research aims to combine the Cox proportional hazard modeling technique with multi-task learning. A widely cited definition of multi-task learning describes it as "an approach to inductive transfer that improves generalization by using the domain information contained in the training signals of related tasks as an inductive bias. It does this by learning tasks in parallel while using a shared representation; what is learned for each task can help other tasks be learned better" [14]. In general, multi-task learning learns from a shared representation across related tasks and ideally, this leads to a decrease in prediction error.

A 2016 paper titled "A Multi-Task Learning Formulation for Survival Analysis" describes a methodology where the survival time prediction problem is formulated into a multi-task learning problem, which then addresses the regression component as a binary classification problem. The model classifies whether an instance's failure has occurred by time $T_i$ or not. The researchers assert that through this shared representation across related tasks, "the dependency between the outcomes at various timepoints" is captured [8].

The objective function for the multi-task model utilizes an $l_{2,1}$-norm penalty in order to learn a shared representation across related tasks while emphasizing only important features and alleviating overfitting. The algorithm described is compared to other standard time-dependent prediction methods using the concordance index and the weighted average of area under the curve (AUC) and shown to outperform them [8]. While the paper discussed aims to extend the functionality of multi-task learning to survival analysis by formulating the problem as a binary classification problem, our team sought to incorporate the benefits of multi-task learning within the standard Cox proportional model formulation.

## METHODOLOGY

### *I. Data Source*

The data used for this analysis was obtained from Electronic Medical Records (EMRs) for CMS patients at the University of Virginia Medical Center. The data covers an 11-month span, with the earliest data point occurring on December 16, 2015 and the latest on November 14, 2016. Among the 1617 individual patients in the dataset, 2373 instances of admissions occurred, 13.4% of which were unplanned readmissions. Patients with multiple admissions were fully used in the analysis as each admission counted as a separate data instance. To narrow down the thousands of diagnosis possibilities, individual ICD-9 codes were converted to diagnoses categories provided by a hash table. The hashing is based on certain qualitative characteristics of each code relating to its main significance. For example, the 426 codes describing various tuberculosis diagnoses are hashed to a single code representing all tuberculosis diagnoses. Thus, the 14,000 possible diagnoses are summarized to 42, which improves modeling by adding more instances to each task group [15].

The EMR dataset has 18 predictors, which spans medical and demographic characteristics. Some of the most significant predictors, with p-value less than 0.05 during tests of variable significance, are included in Table 1 to demonstrate the types of attributes used in modeling.

TABLE I
KEY PREDICTORS IN EMR DATA

| Attribute | Description |
|---|---|
| Median income | Median income of patients within a given |
| | census block |
| Education | Percentage of population in the patient's census |
| | block that completed high school |
| Days since last | Number of previous admissions prior to current |
| discharge | Number of previous admissions prior to current |
| Readmission count | Number of procedures performed |
| Number of procedures | Age of the patient |
| Age | Discharge code with 42 different categories |
| Discharge code | Types of admission: emergency, urgent, or |
| Admissions type | routine |
| Admission source | Sources of admission: 8 different categories |
| Smoking behaviors | Text field of smoking behavior in one of 5 |
| | different categories |
| Admission diagnosis | Condition identified by the physical at the time |
| | of the patient's admission, requiring |
| Principal diagnosis | hospitalization |
| | Condition which occasioned the admission to |
| | the hospital, after study |

Steps were taken to normalize data in order to ensure the algorithms for the Cox proportional and multi-task model converge. All numeric data was normalized into the range of 0 to 1.

To aid model analysis, two new attributes were computed and incorporated: *admission count*, the number of previous admissions prior to current, and *readmission day*, the number of days since patient's last discharge.

*II. Cox Proportional Hazard Model*

Using the preprocessed data as described above, the Cox proportional hazard model was fit using the *coxph* function in the *survival* R package as described in Fox and Weisberg's research on the survival analysis [16]. To condense the model, attributes were selected based on the significant p-value of the full model. The Cox model was then run on this smaller dataset which was made up of seven attributes: the patient's smoking status, sex, age, admissions source, admission category, days since first readmission, and number of times a patient had been admitted prior to admission. Test and training sets were generated and a ten-fold cross validation was used to evaluate the Cox proportional hazard model.

*III. Multi-task Cox Proportional Hazard Model*

While the Cox proportional hazard model is a fundamental technique in survival analysis, it still has its drawbacks. For example, the assumption of proportional hazards suggests that the survival curves of all tasks have a similar shape, which is not always a realistic assumption. Additionally, in order to estimate survival time, the Cox model first needs to estimate a baseline hazard function and use that alongside the estimated hazard ratios to make predictions about survival times. This potentially increases the likelihood of error in the predictions made by the model [8]. Such drawbacks of the Cox model suggest there could be modifications implemented to improve the accuracy of its results. The modification explored by the team is to integrate the concepts of multi-task learning into the Cox model with the aim of producing more accurate predictions of patients' readmission times.

The primary motivation for applying multi-task learning is its ability to learn a shared representation across related tasks and reduce the prediction error of each task. A Ph.D. student in the Systems and Information Engineering department at UVA, Lu Tian, developed the multi-task Cox proportional hazard model R package used for this component of the analysis. The algorithm generates a synthetic dataset that uses the exponential distribution as the baseline hazard function. An estimated coefficient matrix, B, is then generated which can be compared to the underlying real coefficient matrix, *B*, by calculating the difference or drawing the heat maps [17].

In this formulation, a "task" refers to an engineered feature which is derived from a patient's diagnosis and discharge codes. The diagnosis and discharge codes are mapped into a smaller subset of codes in order to reduce the sparsity of that feature matrix. That mapping is accomplished using the hash table referenced in the *Data Sources* section above. Below in (2) is the model's log partial likelihood formulation which is solved in the R package using proximal gradient descent.

$$l(B) = \sum_{k=1}^{K}\sum_{i=1}^{D} B_k^T\, s_{i,k} - d_{i,k} log[\sum_{j \in R_{i,k}} \exp(B_k^T z_j)] + \lambda||B||_{2,1} \quad (2)$$

where $K$ is the set of tasks, $D$ is the set of patients, $B^T{}_k$ is the transposed coefficient vector for a specific task $k$; $s_{i,k}$ is the sum of vectors $z_i$ over all individuals who are readmitted at time $t_i$ for a specific task $k$; $d_{i,k}$ is the number of events at $t_i$ for a specific task $k$, and $z_j$ is the covariate vector [13].

The multi-task model was trained on a training set 75% the size of the EMR data set for hospital readmissions. The coefficients in the resulting coefficient matrix, B, were applied to the patients in the remaining 25% testing dataset depending on which task K a given patient belongs to. This produces predictions for patients' survival time which are used to evaluate the predictive capability of the model.

## RESULTS

After running the ten-fold cross validation for the Cox proportional hazard model, the model resulted in a concordance index of 0.70 with a standard deviation of 0.02. All patients in the same pool have the same estimated baseline function, but with different covariates affecting the predictions. The cumulative hazard rate for the model can be seen below in Figure 1.

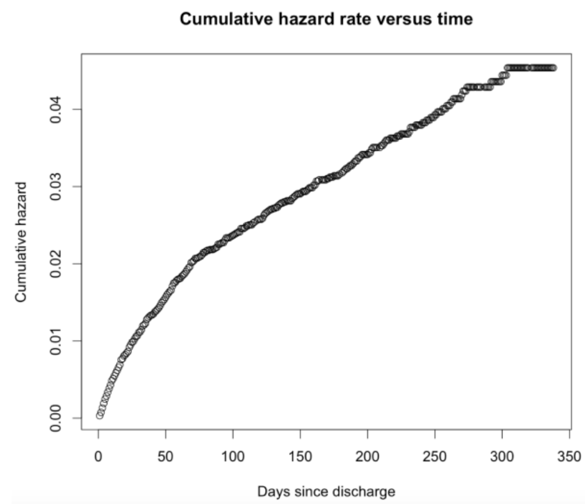


FIGURE I
CUMULATIVE HAZARD RATE FOR THE COX PROPORTIONAL HAZARD MODEL

The multi-task Cox proportional model has different baseline hazard functions for patients in different task groups. After running cross validation, the model exhibited a concordance index of 0.52.

## DISCUSSION

The concordance index of both the Cox proportional hazard model and the multi-task Cox proportional hazard model, 0.70 and 0.52, respectively, fall below the 0.72 concordance index of the Random Survival Forest. The concordance index (CI) measures overall predictability for survival models by calculating the proportion of pairs within the data where the instance with a longer survival time is matched with a higher predicted probability of survival [18]. When applied to two patients facing readmission, the CI calculates if the patient who the model predicted to stay out of the hospital longer actually had a longer period of time until a readmission. Thus, the higher CI for the RSF model indicates it provides stronger predictors than both the Cox and multi-task models.

While the RSF model performed slightly better than the standard Cox model, both models performed significantly better than the multi-task Cox model. There are a number of possible explanations that could provide insight into why that is. First, the tasks by which patients were grouped in the multi-task model were the patients' diagnoses codes. A number of the diagnosis codes were only found once or twice in the training dataset which means that the *B* coefficient vector for that task was based on just a few observations. This could pose problems with regards to how applicable or representative that coefficient vector is for its respective task. Second, the dataset as a whole was relatively small and it is conceivable that the multi-task formulation is better suited for a bigger dataset when compared with the RSF model or the standard Cox model. Third, it is possible that our choice of tasks by which the patients are grouped is not best suited for the readmissions problem. There could be other factors that would provide better predictive power of readmissions time when grouped together into a shared representation within the multi-task model.

Overall, the results appear similar to other readmission prediction studies. Padhukasahasram et al.'s 2015 study of clinical variables impact on readmission following a heart failure featured similar differences between Cox proportional hazard and RSF models: Their Cox model had a 0.61 CI and their RSF model a 0.67 CI [19]. This increase in the RSF model's predictability parallels findings from our research and could point to RSF being better suited towards survival analysis, especially when applied to the readmissions problem.

## CONCLUSION

Significant benefits exist in predicting readmission risk for the 30 day period following discharge, as it strengthens medical providers' abilities to determine the most appropriate follow-up care. Locus Health, the outpatient care center partnering with UVAMC, may particularly benefit from the model when choosing which follow-up care procedures best fit a certain patient's recovery timeline. With approximately 131 projected readmissions prevented over an 11-month period, additional predictive models may help to grow this statistic even more rapidly going forward. Other healthcare professional could benefit too--a primary care physician could evaluate risk projections to determine the point in time when s/he should check-in on a discharged patient's recovery, and medical social workers could be more encouraged to understand a patient's circumstances after seeing their readmission risk projections. These actions could lead to long-term gains for a patient's overall wellness.

Despite the potential benefits of using predictive models for readmissions, limitations exist with their implementation. A variety of health care professionals interacting with the model means each would need training on how to apply its output to patients. It will take time to train these professionals, and in turn, it will take time for them to learn how to fully utilize the model within their field. Some professionals may question the utility of using the model's output because they do not understand the theoretical backbone of the model or its output. Some may also place greater trust in their own judgment and experience than the output of a model they cannot understand. Additionally, there is the bigger problem of generalizability, where a lot of the models can be found to perform well on certain datasets, but that performance does not carry over to other populations of patients for a multitude of reasons. Such reasons can include differences demographic, social, or geographic factors, nature of the patient populations and medical practices. These are all legitimate obstacles to successfully implementing predictive models, and appropriate steps should be taken to ensure all issues are addressed.

Predictive models will continue to become more useful in reducing readmission rates nationwide. As other hospitals simultaneously advance in assessing readmissions, the national average may fall to the same degree as the UVAMC's rate falls. Thus, UVA's comparison to the national average may remain relatively constant. Though UVA's Medicare and Medicaid financial penalties may stay around the same level, nationwide reduction in readmissions should be seen as an overall success for the healthcare realm. Fewer readmissions means less federal money passed between hospitals and CMS, allowing those funds to be better allocated for other public purposes.

## FUTURE WORK

While the multi-task model had a lower performance measure compared to the standard Cox proportional hazard model, it is possible that testing the algorithm on a larger or more specific dataset may result in a higher concordance index. It is also possible that choosing other attributes as tasks by which the patients are grouped could lead to better results from the multi-task formulation. Additionally, testing this implementation of the multi-task Cox on larger datasets can help fine-tune the algorithm and improve it for the purpose of providing more accurate predictions. Due to the limited amount of time and familiarity with the multi-task package, we were not able to implement these suggestions, but we are hopeful it will result in more accurate predictions going forward.

## ACKNOWLEDGEMENT

The researchers wish to express their gratitude to the University of Virginia Medical Center data scientists, Dr. Robert Yerex and Dr. Jon Michel, for allowing us to work with them to improve the hospital's readmission risk model and to Dr. Tracey Hoke, Chief of Quality and Performance Improvement, for serving as executive sponsor. The support of other domain experts was instrumental as well, particularly from Dr. Jason Lyman, Matthew Kaufmann, and Dr. Paul

Helgerson from UVAMC, and Patti Dewberry and her team at Locus Health.

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