Predicting Risk-of-Readmission for Congestive Heart Failure Patients: A Multi-Layer Approach

Kiyana Zolfaghar, MS¹, Nele Verbiest, MS², Jayshree Agarwal, MS¹, Naren Meadem, BS¹, Si-Chi Chin, PhD¹, Senjuti Basu Roy, PhD¹, Ankur Teredesai, PhD¹, David Hazel, MS¹, Paul Amoroso, MD³, Lester Reed, MD³
 ¹Institute of Technology, CWDS, University of Washington Tacoma, WA; ²Department of Applied Mathematics, Computer Science and Statistics, Ghent University, Belgium; ³Multicare Health System, Tacoma, WA

Abstract

Mitigating risk-of-readmission of Congestive Heart Failure (CHF) patients within 30 days of discharge is important because such readmissions are not only expensive but also critical indicator of provider care and quality of treatment. Accurately predicting the risk-of-readmission may allow hospitals to identify high-risk patients and eventually improve quality of care by identifying factors that contribute to such readmissions in many scenarios. In this paper, we investigate the problem of predicting risk-of-readmission as a supervised learning problem, using a multi-layer classification approach. Earlier contributions inadequately attempted to assess a risk value for 30 day readmission by building a direct predictive model as opposed to our approach. We first split the problem into various stages, (a) at risk in general (b) risk within 60 days (c) risk within 30 days, and then build suitable classifiers for each stage, thereby increasing the ability to accurately predict the risk using multiple layers of decision. The advantage of our approach is that we can use different classification models for the subtasks that are more suited for the respective problems. Moreover, each of the subtasks can be solved using different features and training data leading to a highly confident diagnosis or risk compared to a one-shot single layer approach. An experimental evaluation on actual hospital patient record data from Multicare Health Systems shows that our model is significantly better at predicting risk-of-readmission of CHF patients within 30 days after discharge compared to prior attempts.

Introduction

With the overwhelming increase in available health care data, analyzing and mining this data has gained more interest over the last decade. Improving awareness, personalizing medical treatments and ameliorating health care standards are only a few examples of opportunities that result from mining health care data¹.

In this work, we focus on building a predictive model to enhance quality of care² for patients with cardiac heart failure. The main goal is to predict the level of risk of patients being discharged after a Congestive Heart Failure (CHF) in order to assess if they are likely to be at high risk of readmission within the next 30 days. We approach this as a *classification problem to classify patients into high or low risk given historical discharge history data along with variety of other parameters*. We leverage historic patient data that contains admission-readmission histories of CHF patients. Moreover, hospital readmission is expensive and generally preventable³. If CHF readmission could be predicted accurately, hospitals would invest more purposefully in improving hospital care by reducing risk of infection, reconciling medications, educating patients on what exact symptoms to monitor, and assess readiness of patients for discharge⁴. At first, the 30 day window seems to be arbitrary, but it is indeed a clinically meaningful time window for hospitals, and the Center for Medicare and Medicaid Services (CMS) has started using the 30 day all cause heart failure readmission rate as a publicly reported efficiency metric. Moreover, all cause 30 day readmission rate for patients with CHF has increased by 11 percent between 1992 and 2001¹⁵.

Predicting if patients discharged with CHF will be readmitted within 30 days is traditionally approached as a single classification task. We observe two main drawbacks of this approach: (a) firstly, classification of risk of readmission is highly imbalanced, as can be seen from Figure 1, and is hence inherently difficult to solve⁵, and (b) secondly, (COMPLETE THIS HERE) Traditional classification methods will generally tend to assign most of the patients to the majority class (no readmission), as the training data consists mostly of majority instances. Another issue is in including all patients discharged with CHF to build the classification model might not be meaningful, as patients that were discharged after a long length of stay can have characteristics that are totally different from patients that were discharged after a short length of stay , and are hence irrelevant for the 30 days classification task.



Figure 1: The number of times a patient was readmitted within 30 days after discharge from CHF in a span of 3 years.

In this paper we address these drawbacks by introducing a multi-layer classification strategy. The main idea is: we first build a rough model that predicts if patients will be readmitted within a given time window longer than 30 days, and then use a more refined model to predict if patients will be readmitted within 30 days. Specifically, in order to predict if any patient discharged after CHF will be readmitted within 30 days, we first use a coarse grain model to predict if the patient is likely to be readmitted at all (in any reasonable timeframe). If not, we can mostly conclude that the patient will be readmitted within 30 days (a very short timeframe). Else, we predict if the patient will be readmitted within a large time window. If not, than we can conclude that the patient will not be readmitted within 30 days. If the outcome is that the patient will be readmitted within the large time window, we can use the more refined model to predict if the patient will be readmitted within 30 days.

This multi-layer classifier allows for flexibility in many ways. The main advantage is that we can use different models for respective granularity of problems. If we use different classifiers for different layers, we can use different features for each layer; and the classification tasks can be more refined as it only considers patients in the training data that were readmitted within the large time window. The second advantage is that we can split up the imbalanced classification problem in two more or relatively more balanced classification problems.

The main contributions of this paper are:

- We introduce a multi-layer classifier to predict if patients are likely to be readmitted within 30 days after being discharged from CHF
- We perform an experimental study using a real-world data set provided by the Multicare Health Systems

The remainder of this paper is structured as follows. In the next Section, we describe our multi-layer approach in detail, and describe the classifiers and feature selection methods that are used in the layers. Next, we evaluate the performance of our approach in the experimental Section, and compare it with state-of-the-art methods. Afterwards, we study related work, and we conclude and suggest further research directions in the concluding Section.

Multi-layer Classification for Readmission of Congestive Heart Failure Patients

In this section we propose a multi-layer classifier method for predicting readmission of congestive heart failure patients. Instead of tackling the classification problem at once, we divide it in three sub-problems, as depicted in Figure 2. For a new patient discharged after CHF treatment, we first predict if she will ever be readmitted to the hospital. If the prediction is that the patient will likely never be readmitted, we are done with the prediction task. If

the outcome is that the patient may be readmitted (i.e. predicted yes), we use another model (layer) to predict if the patient will be readmitted within 60 days. Again, if the outcome is no, this means that the patient will not be readmitted within 60 days, and hence we output that the patient will not be readmitted within 30 days neither. If the outcome is again a yes, we use yet another model (hence multi-layer) to predict if the patient will be readmitted within 30 days. The outcome of this final classification is then returned as the final classification.



Figure 2 Subdivision of the classification problem into multiple layers.

Training data that is used in each layer is different. The upper layer uses all the training data. At the second layer, only the patients in the training data that are readmitted are used. In the last layer of the problem, only the patients that are admitted within 60 days are used. As a result, the training data that is used in the second and final layer is more refined than the original data. The purpose of this is to provide each sub-problem only with the relevant data. For example, if we want to predict if a patient will be readmitted within 30 days, the information about patients that will never be readmitted is not relevant and might disturb the classification.

Another important advantage of this approach is that the highly imbalanced problem is divided into three more or less balanced problems. The data distribution is depicted in Figure 3. In general, a classification problem is called imbalanced if its Imbalance Ratio (IR, number of majority instances divided by the number of minority instances) is more than 2. In the original problem, the positive class (patients readmitted within 30 days) covered 1477 patients, while the majority class covered 8293 patients. The imbalance ratio of this problem is 5.6, making it severely imbalanced. Number of patients that was never readmitted is 5503 and the total number of patients considered is 9770, resulting in an IR of 1.7 leading to a more balanced problem that is generally easier to solve. The threshold 60 at the second layer of the multi-classifier was chosen to balance the second layer problem, such that the IR of the second layer is 1. The number of patients that were readmitted within 30 days is 1477, so the IR of the final layer is 1.4. We conclude that using this multi-layer approach, the heavily imbalanced original problem is divided into subtasks (layers) that are more or less balanced.



Figure 3: Distribution of the patients based on the number of days until readmission after CHS. By dividing the problem in three parts, each of the subtasks is balanced.

Furthermore, we can consider different features in each sub-problem. For instance, features which are good to predict if a patient will ever be readmitted or not, might not be relevant features to predict if the patient will be readmitted within 30 days. Therefore, we apply feature selection in every layer of the multi-layered classifier. As a result, each layer will work with features that are suited for the corresponding classification task.

The feature selection technique that we use in this paper is the Chi-square $test^6$, as this technique has proven to be successful in earlier works. This test calculates for each feature a score that expresses its relevance with respect to the decision class, and then decides based on this score which features to retain.

Finally, we can also use different classifiers for the different sub-problems. There are two advantages related to this property. The first one is that it can occur that one classifier is well suited for one classification problem but not for the other. For instance, one classifier can work well for the second layer problem, but not for the third layer problem. Secondly, some classifiers require a longer running time than others, and it might not always be feasible to apply them to each layer of the problem. However, it is possible to apply these more involved classifiers to the final layer of the classification problem. We hope that using a more refined classifier for the final layer of our approach will improve classification results.

We propose two different multi-layer classifiers, as described in Table 2. The first classifier, to which we will refer to as MLC1, is a multi-layer classifier that uses the Naïve Bayes (NB^7) classifier in each layer of the problem. The second classifier, called MLC2, uses NB in the first two coarse layers of the problem, and then uses a Support Vector Machine (SVM^8) classifier for the final classification problem.

We work with NB because it is a fast and simple model that has shown to be effective in many real-world problems. The SVM classifier is more time-consuming, but it is generally more accurate. Therefore, we use it in the last layer of one of the multi-layer classifiers.

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	MLC1	MLC2		
Predicting if patient will be ever	NB	NB		
Teaumitteu				
Predicting if patient will be	NB	NB		
readmitted within 60 days	ND	ND		
Predicting if patient will be	ND	SVM		
readmitted within 30 days	IND	5 V M		

Table	1:	The	classifiers	(NB c	or SVM)) that are use	d in each	laver o	of the two	multi-laver	· classifiers.
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Experimental Evaluation: Set-up

The dataset used to derive our readmission prediction model is provided by Multicare Health System (MHS). We are given a set of tables where each table contains data related to the patients. Hospital encounters with discharge diagnosis of CHF (primary or secondary) are considered as the potential index admission due to CHF. We only

consider patients with a discharge diagnosis of the International Classification of Diseases, 9th Revision, Clinical Modification Codes (ICD-9 CM) related to CHF, listed in Table 2.

ICD-9 CM codes	Description
402.01	Malignant hypertensive heart disease with heart failure
402.11	Benign hypertensive heart disease with heart failure
402.91	Unspecified hypertensive heart disease with heart failure
404.01	Malignant hypertensive heart and kidney disease with
	heart failure and with chronic kidney disease stage I
	through stage IV, or unspecified
404.03	Malignant hypertensive heart and kidney disease with
	heart failure and chronic kidney disease stage V or end
	stage renal disease
404.11	Benign hypertensive heart and kidney disease with heart
	failure and with chronic kidney disease stage I through
	stage IV, or unspecified
404.13	Benign hypertensive heart and kidney disease with heart
	failure and chronic kidney disease stage V or end stage
	renal disease
404.91	Unspecified hypertensive heart and kidney disease with
	heart failure and with chronic kidney disease stage I
	through stage IV, or unspecified
404.93	Unspecified hypertensive heart and kidney disease with
	heart failure and chronic kidney disease stage V or end
	stage renal disease
428.XX	Heart Failure codes

 Table 2: The ICD-9 CM codes for CHF

All the patients can be identified by a unique patient id and each hospital encounter is uniquely identified by an admission id. Multiple admissions (i.e., readmissions) of the same patient can be identified by using the patient id. Our entity of observation is each CHF hospital encounter and we consider only the admissions when a patient is discharged to home to exclude inter hospital transfers. Admissions encountering in-hospital deaths are not included in our analysis because we are more interested in predicting readmissions. We calculate the days elapsed between the last discharge due to CHF and next admission in order to identify if the readmission has occurred within 30 days. The dataset consists of CHF hospitalization for patients discharged since 2009. It provides information of 6348 patients diagnosed with CHF and number of hospital encounters generated by these patients during 2009-2012 is 11383. As mentioned earlier, various supporting tables are provided to get a complete understanding the patients related to heart failure and to identify the attributes to be used as predictor variables in modeling. The detailed description of some of the attributes is given in Table 3.

The key socio-demographic factors related to patients are, gender, race, marital status. Some of the other important factors pertinent to CHF are ejection fraction which represents the volumetric fraction of blood pumped out of the ventricle with each heartbeat, blood pressure, primary and secondary diagnosis, other comorbidity variables, APR-DRG code (All Patient Refined Diagnosis Related Groups Definition; a classification system that classifies patients according to reason of admission) for severity of illness and APR-DRG code for risk of mortality. Information about the discharge disposition of patients like the discharge status, discharge destination, length of stay and follow-up plans are also found to be correlated to CHF readmissions. In addition, 34 cardiovascular and comorbidity attributes¹⁴ mentioned in Table 3 are also used. Based on our initial understanding we observed that ejection fraction has about 59% of missing values followed by APR-DRG code for severity of illness (13.3%) and blood pressure (12.6%). We imputed the missing value of ejection fraction and after removing the instances with other null values; our final dataset consists of 9770 instances on which the model is built.

Table 3: Description	of different	attributes
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Variable	Туре	Mean/No. of Domain Values
Age	Numeric	69
Gender	Categorical	2(M, F)
Marital status	Categorical	9 such as married, divorced
Ethnic group	Categorical	9 such as Caucasian, Asian, African-American
Discharge follow-up plan	Categorical	7 such as 2 days, 5 days
Discharge destination	Categorical	70
Discharge status	Categorical	15 such as discharged to home, discharged to rehab facility
Admit source	Categorical	6 such as transfer from hospital, emergency room
Admit type	Categorical	4 such as elective, emergency
Blood Pressure	Categorical	9
Ejection fraction value	Numeric	48.63
Secondary diagnosis count	Numeric	16.56
Discharge APR-DRG Severity of illness	Categorical	4 such as 1(least severe), 2, 3, 4(most severe)
Discharge APR-DRG Risk of mortality	Categorical	4 such as 1(least severe), 2, 3, 4(most severe).
Length of stay	Numeric	5
IsHFPrimary	Categorical	2(Y.N)
Congestive heart failure	Categorical	2(0,1)
Acute coronary syndrome	Categorical	2(0,1)
Arrhythmias	Categorical	2(0,1)
Cardio-respiratory failure and shock	Categorical	2(0,1)
Valvular and rheumatic heart disease	Categorical	2(0,1)
Vacular or circulatory disease	Categorical	2(0,1)
Chronic atherosclerosis	Categorical	2(0,1)
Other and unspecified heart disease	Categorical	2(0,1)
Heminlegia paraplegia paralysis functional	Categorical	2(0,1)
disability	Categorical	2 (0,1)
Stroke	Categorical	2 (0 1)
Renal failure	Categorical	2(0,1)
COPD	Categorical	2(0,1)
Diabetes and DM complications	Categorical	2(0,1)
Disorders of fluid/alectrolyte/acid base	Categorical	2(0,1)
Other urinary tract disorders	Categorical	2(0,1)
Decubitus ulcer or chronic skin ulcer	Categorical	2(0,1)
Other gastrointestinal disorders	Categorical	2(0,1)
Pentic ulcer hemorrhage other	Categorical	2(0,1)
specified gastrointestinal disorders	Categoricai	2 (0,1)
Severe hematological disorders	Categorical	2(01)
Nenhritis	Categorical	2(0,1)
Dementia and senility	Categorical	2(0,1)
Metastatic concer and soute	Categorical	2(0,1)
leukemia	Categoricai	2 (0,1)
Cancer	Categorical	2(01)
Liver and biliary disease	Categorical	2(0,1)
End stage renal disease or dialysis	Categorical	2(0,1)
Asthma	Categorical	2(0,1)
Asuma Iron deficiency and	Categorical	2(0,1)
other/unspecified anomies and	Categoricai	2 (0,1)
blood disease		
Broumonia	Catagoriaal	2(01)
Drug/alcohol abusa/dapandanga/payahasia	Categorical	2(0,1) 2(0,1)
Major pysch disorders	Categorical	2(0,1)
Dapression	Categorical	2(0,1)
Other psychiatria disorders	Categorical	2(0,1)
Ethnoric of lung and other share's lung disc.		2(0,1)
Protoin colorio molecuteritice		2(0,1)
FIOLEIN-CAIOFIE MAINULTUON	Calegorical	(2,0,1)

We compare our model with two relevant baseline methods. Both baseline methods first apply the same feature selection method to the data as in our model, namely Chi-Square. After that, we use both NB and SVM to classify the data. Both baseline methods use all the data to predict if a patient discharged from CHS will be readmitted within 30 days.

Before running the algorithms on the data, we first impute missing values in the Ejection Fraction feature. We do this both for the baseline methods as for our proposed method. The instances that have missing values in other features are removed from the dataset. As we do this for both the baseline methods and our proposed multi-layer classifier, we obtain a fair comparison. The reason why we only impute the missing values in the Ejection Fraction feature is that this feature has a high percentage of missing values (about 60 percent) and that this approach has proven to work well in preliminary experiments⁹.

We perform a 10 fold cross validation procedure, that is, the data is divided into 10 equal folds, and each fold is considered as test data, that is classified using a model that is built on the remaining 9 folds, called the training data. As each fold is considered once as test data, we obtain one single classification outcome for each instance in the set.

The outline of the experiments is depicted in Figure 4.



Figure 4: Structure of the experimental set-up

Experimental Evaluation: Results

In this section, we present and discuss the results obtained with our multi-layer classification approach, and compare it to the baseline approaches. In Table 2, we show the confusion matrix values for all methods. The positives refer to the patients that are readmitted within 30 days to the hospital after discharge from CHS, while the negatives refer to all other patients. For instance, True Positives refers to the patients that were readmitted within 30 days to the

hospital, and that were also predicted by the respective classifier to be readmitted within 30 days. On the other hand, False Negatives refers to patients that were readmitted within 30 days to the hospital, but for which the classifier predicted that the patient would not be readmitted within 30 days. These numbers give a good insight in the performance of the classifier, especially because the considered problem is highly imbalanced. Only reporting accuracy would give a false image of the results.

	True Positives (TN)	False Positives (FP)	True Negatives (TN)	False Negatives (FN)
Baseline NB	33	116	8177	1444
Baseline SVM	1	5	8288	1476
MLC1	457	1546	6747	1020
MLC2	464	1574	6719	1013

Table 2:	Confusion	matrix	results	of the	- 4	classifiers.
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Recall that the goal of our approach was to better detect patients that will be readmitted within 30 days to the hospital. As we can see from Table 2, we do succeed in this. While the baseline methods NB and SVM only detect respectively 33 and 1 out of 1480 positive patients, our new classifier detects about one third of the patients that will be readmitted within 30 days. Of course, this comes with a higher false positive rate, but this is less problematic than not recognizing patients that will be readmitted within 30 days, this means that the hospital possibly undertakes unnecessary measures for this patient to prevent readmission. These measures will cause additional costs, but they are probably less weighty than costs associated with hospital readmission.

A remarkable conclusion that we can draw from this chart is that the SVM clearly performs worse as baseline method. Although SVM is generally an accurate classifier, it is not able to handle this imbalanced problem well. NB can deal with the imbalanced problem slightly better, but it is only able to detect 2 percent of the patients that will be readmitted within 30 days.

The performances of the two multi-layer classifiers that we proposed do not differ much, probably because the classification in the two first layer are determining for the further final classification. MLC2 is slightly better at detecting patients that will be readmitted within 30 days, but this result is not significant.

Related Work

An increasing body of literature attempts to develop and validate the predictive models for risk of hospital readmission. The studies cover readmission due to various diseases (heart failure, pneumonia¹⁰, asthma¹¹) and many of them report the outcome for 30 days, though there do exist few models built on different time intervals (60 days¹², 90 days¹³, and even 1 year¹⁴). Each of the developed models exploit different predictor variables and can be classified as using real time data or retrospective data based on the time at which these variables were assessed during an index hospitalization.

One of the significant efforts developed a hierarchical regression model to calculate hospital-specific, riskstandardized, 30-day all-cause readmission rates for Medicare patients hospitalized with heart failure¹⁵. The model used administrative claims data and focused on primarily cardiovascular and comorbidity variables. The patients used in modeling were limited to the ones more than 65 years old.

In another related work, a real time predictive model is built on the socio-demographic factors of hospitalized heart failure patients to predict the risk of readmission within 30-day time window¹⁶. Although the model demonstrated good discrimination for 30-day readmission, the dataset size used was much smaller (1372 patients).

In another study, a regression model is developed using Medicare claims along with clinical data of patients discharged between 2004 and 2006¹⁷. This work focused on patients older than 65 years old and included 24,163 patients from 307 hospitals in their analysis. Our dataset consists of fewer patients but includes more type of data sources.

Another interesting approach develops predictive models for hospital readmission within 30 days that incorporate semantically meaningful derived data elements representing phenotypes¹⁹. Using this approach, the number of features is reduced drastically, and the data contains less noise. Moreover, clinical knowledge can be introduced into the model and the underlying data representation is abstracted. This preprocessing facilitates the application of data mining algorithms.

To the best of our knowledge, there is only one publication that studies a multi-layer classifier similar to our approach. In this study¹⁸, the authors divide the problem of power transformer fault diagnosis into several subproblems. The difference with our work is that the authors use the same model for each layer, whereas we propose to use different features and classifiers in each layer.

Conclusion and Future Work

In this paper, we introduced a multi-layer classifier to predict if patients discharged from CHS will be readmitted to the hospital within 30 days. Instead of considering this classification as a single task, we subdivide the problem in different subtasks. The advantages of this approach are that we can use different models, feature subsets and training data for each classification subtask, and that the subtasks are more balanced than the original task. An experimental evaluation on a real-world dataset shows that our approach is better at detecting the patients that will be readmitted to the hospital within 30 days than baseline approaches.

In the future we would like to elaborate more on the different models that are used for the subtasks. Currently, we use the same feature selection method in each layer, and we only use two different classifiers over all layers. We want to exploit the fact that the subtasks are smaller classification problems and that we can run more complicated and time-consuming algorithms on them. Moreover, we want study the balance between detecting the patients that will truly be readmitted within 30 days and the cost that is related to the patients that were falsely classified as being readmitted within 30 days.

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References

- 1. Steinbrook R. Personally Controlled Online Health Data- The Next Big Thing in Medical Care? New England Journal of Medicine. 2008;358.16:1653-1656.
- 2. Benbassat J, Taragin M. Hospital Readmissions as a measure of Quality of Health Care: Advantages and Limitations. Archives of Internal Medicine. 2000;160.8:1074-1081.
- 3. Giordano A, Scalvini S, Zanelli E, Corrà U, Longobardi GL, Ricci VA, Baiardi P, Glisenti F. Multicenter randomized trial on home-based telemanagement to prevent hospital readmission of patients with chronic heart failure. International Journal of Cardiology. 2009;131.2:192-199.
- 4. Philbin EF, Di Salvo TG. Prediction of hospital readmission for heart failure: development of a simple risk score based on administrative data. Journal of the American College of Cardiology. 1999;33.6:1560-1566.
- 5. Japkowicz N, Shaju S. The Class Imbalance Problem: A Systematic Study. Intelligent Data Analysis. 2002;6.5:429-449.
- 6. Han J, Kamber M. Data mining: concepts and techniques. Morgan Kaufmann. 2006.
- 7. Hand DJ, Yu K. Idiot's Bayes-not so stupid after all? International Statistical Review. 2001;69.3:385-399.
- 8. Cortes C, Vapnik V. Support-Vector Networks. Machine Learning. 1995:20.3:273-297.
- 9. Meadem N, Zolfaghar K, Agarwal J, Chin S, Basu Roy S, Teredesai A, Hazel D, Amoroso P, Reed L, Predicting Risk of Readmission for Congestive Heart Failure Patients. Under review KDD 2013.

- 10. El Solh AA, Brewer T, Okada M, Bashir O, Gough M. Indicators of Recurrent Hospitalization for Pneumonia in the elderly. Journal of the American Geriatrics Society, 2004; 52:2010-2015.
- 11. Bloomberg GR, Trinkaus KM, Fisher EB, Musick JR, Strunk RC. Hospital Readmissions for Childhood Asthma, A 10 Year Metropolitan Sudy. American Journal of Respiratory and Critical Care Medicine 2003;167.8: 1068-1076.
- 12. Cuffe MS, Califf RM, Adams KF Jr., Benza R, Bourge R, Colucci WS, Massie BM, O'Connor CM, Pina I, Quigg R, Silver MA, Gheorghiade M. Journal of the American Medical Association. 2002;287.12:1541-1547.
- Spyropoulos AC, Jay L. Direct medical costs of venous thromboembolism and subsequent hospital readmission rates: an administrative claims analysis from 30 managed care organizations. Journal of Managed Care Pharmacy. 2007;13.6:475-486.
- Saunders J, Ballantyne GH, Belsley S, Stephens DJ, Trivedi A, Ewing DR, Iannace VA, Capella RF, Wasilewski A, Moran S, Schmidt HJ. One-year Readmission rates at a high volume bariatric surgery center: laparoscopic adjustable gastric banding, laparoscopic gastric bypass, and vertical banded gastroplastyroux –enY gastric bypass. Journal of Obesity Surgery. 2008;18.10:1233-1240.
- Krumholz HM, Normand SLT, Keenan PS, Lin ZQ, Drye EE, Bhat KR, Wang YF, Ross JS, Schuur JD, Stauer BD. Hospital 30-day heart failure readmission measure methodology. Report prepared for the Centers for Medicare and Medicaid Services.
- 16. Amarasingham R, Moor BJ, Tabak YP, Drazner MH, Clark CA, Zhang S, Reed WG, Swanson TS, Ma Y, Halm EA. An automated model to identify heart failure patients at risk for 30-day readmission or death using electronic medical record data. Journal of Medical Care. 2010;10:981-988.
- 17. Hamill BG, Curtis MH, Fonarow GC, Heidenreich PA, Yancy CW, Peterson ED, Hernandez AF, Incremental value of clinical data beyond claims data in predicting 30-day outcomes after heart failure hospitalization. Circulation. Cardiovascular Quality Outcomes. 2011;4.4:60-67.
- 18. Ganyun LV, Haozhong C, Haibao Z, Lixin D. Fault diagnosis of power transformer based on multi-layer SVM classifier. Journal of Electric Power Systems Research. 2005;74.1:1-7.
- 19. Cholleti S, Post A, Gao J, Lin X, Bornstein W, Cantrell D, Saltz J. Leveraging Derived Data Elements in Data Analytic Models forUnderstanding and Predicting Hospital Readmissions. AMIA annual Symposium Proceedings. 2012:103-111.