Assessing the Predictability of Hospital Readmission Using Machine Learning

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Abstract

Unplanned hospital readmissions raise health care costs and cause significant distress to patients. Hence, predicting which patients are at risk to be readmitted is of great interest. In this paper, we mine large amounts of administrative information from claim data, including patients demographics, dispensed drugs, medical or surgical procedures performed, and medical diagnosis, in order to predict readmission using supervised learning methods. Our objective is to gain knowledge about the predictive power of the available information. Our preliminary results on data from the provincial hospital system in Quebec illustrate the potential for this approach to reveal important information on factors that trigger hospital readmission. Our findings suggest that a substantial portion of readmissions is inherently hard to predict. Consequently, the use of the raw readmission rate as an indicator of the quality of provided care might not be appropriate.

Introduction

A hospital readmission is defined as an admission to a hospital or a healthcare setting within a certain time frame, following an original hospital stay. A readmission can occur at either the same hospital or a different hospital, and can involve planned or unplanned surgical or medical treatments (Stone and Hoffman 2010). Different time frames have been used for the analysis of readmission in the literature (Heggestad and Lilleeng 2003). However, in the clinical literature, readmissions typically refer to hospital admissions within 30 days following the initial discharge. Readmissions contribute to a significant proportion of total inpatient spending in many countries. In the United States, they account for \$17.4 billion per year (Catlin 2008). In Canada, readmissions to acute care cost an estimated \$1.8 billion per year (Canadian Institute for Health Information 2012). While in many cases readmission is an unavoidable cost, in other cases readmission is due to some system failure and so the associated costs could potentially be recovered.

Some of the causes of hospital readmission include patient-level factors such as age and multiple chronic conditions; hospital and health system-level factors such as the timeliness of post-discharge followup, nurse workload, coordination of care after discharge; or medical errors and adverse events that occurred during the initial hospitalization. To reduce hospital readmissions due to providing poor care, hospitals are penalized for excessive rates of readmissions according to new policies to penalize low quality care (Benbassat and Taragin 2000; Billings, Mijanovich, and Wennberg 2006). However, the effectiveness of such policies is not known. Besides, in practice, the evidence describing the relationship between the hospitals' role in readmission remains fragmented and mainly qualitative. Unfortunately, whatever the cause, the risk of future readmission is considerable and the need to improve our understanding about the determinants of readmission is clear. Knowledge about readmission risk factors could also be used to help target a more focused delivery of care and resources to the patients at greatest risk and provide better quality healthcare.

Many factors have been suggested by researchers as potentially important in the prediction of hospital readmission, but the utility of such factors has not been widely studied due to data accessibility issues and methodological issues. Typically, risk factors for readmission are identified using traditional hypothesis-driven statistical methods such as logistic regression. However, limitations become apparent in these approaches as the scope of these studies expand to include a very large range of variables, which can be obtained as a result of the new electronic medical records management in future.

Our goal is to improve the understanding of the determinants of readmission using a large number of variables including drug classification codes, diagnostic codes, medical and surgical procedure codes. We deploy machine learning algorithms that can coherently incorporate this information in the parameters of a model and potentially overcome the analytical challenges that hypothesis driven methods face in this situation. The inclusion of prescription drugs in this research is based on the hypothesis that the type, the variety, and the dose of drugs can indicate patient's health status or severity of illness. There is consensus that the use of appropriate drugs can reduce the chance of readmission. For instance, in one study, it was found that patients with asthma who receive regularly inhaled corticosteroids have 31% fewer hospital admissions and 39% fewer readmissions than asthma patients who do not use this type of medication (Suissa, Ernst, and Kezouh 2002). However, it is not known which medications can be effective reducing readmission in general, or which medications are effective predictors of readmission.

The data set we use has over 20,000 features, which poses some challenges for the classical machine learning methods. Therefore, we investigate dimensionality reduction techniques to select the most promising features. Taking into account the entire spectrum of drugs in a predictive model is not feasible. Grouping drugs in a hierarchy based on pharmaceutical classification code systems addresses the dimensionality problem, but there is no evidence on how well this grouping works for this task. We investigate for the first time the efficiency of classification code systems for drugs, diagnosis, and procedures for predictive models, and compare them with standard machine learning approaches for feature selection. The number of variables that we consider is very high in our data compared to other studies, and we focus on methods that maintain interpretability and help pinpoint drugs that influence readmissions most.. The use of prescription medications can also be helpful in revealing possible medical errors related to appropriateness of drug utilization and the medication reconciliation at the care providing institution, although this topic is not the focus of this paper.

Background on Hospital Readmission Models

In this section we review existing hospital readmission prediction models with respect to the factors they consider and the methodology utilized. A review of published studies on readmission analysis shows that most studies in the literature focus primarily on the role of demographic information such as age and gender, medical comorbidity, and prior health services utilization and prior hospitalizations in readmission risk (Krumholz, Normand, and Keenan 2008b; 2008a; 2008c). Data from these studies show that readmission rates are associated with age, patient comorbidities, and other factors such as length of stay in the hospital. The likelihood of a readmission increases with the patient history of medical readmissions. The highest readmission rates have been observed in geriatric patients, mainly with heart failure and chronic obstructive pulmonary disease (Hernandez, Greiner, and Fonarow 2010). However, the specific reasons such persons are readmitted still needs further exploration. Some studies used an index, named LACE, to score the risk of readmission (Walraven et al. 2010; Gruneir et al. 2011) in clinical settings. LACE is defined by the following factors: length of stay L; acuity of the admission A; comorbidity of the patient (measured with the Charlson comorbidity index score) C; and emergency department use E (measured as the number of visits in the six months before admission). The value of this index is zero for no risk, and higher (up to 19) for more risk of future readmissions. However, this index is considered to be a poor tool for predicting 30-day readmission (Cotter et al. 2012). Some researchers believe that models which consider factors such as medical comorbidities and basic demographic data are much better able to predict mortality and unavoidable readmission rather than readmission in general (Hammill, Curtis, and Fonarow 2011; Amarasingham, Moore, and Tabak 2010; Walraven et al. 2010). There are not many validation studies to show which readmission records are unavoidable. We could only find one validated prediction model that explicitly examined potentially preventable readmissions as an outcome, and it found that only about one-quarter of readmissions were clearly preventable (Halfon et al. 2006).

It has been argued that incorporating different observations such as the attributes related to socioeconomic status, and the patient's overall health can provide novel insights into causes for readmission (Amarasingham, Moore, and Tabak 2010). Similarly, researchers suggest that the analysis of readmission based on prescription drugs can potentially provide more understanding of the disease severity and impact of drugs (such as adverse events) on predicting readmission (Morrissey et al. 2003). A few studies considered variables associated with the severity of illness, patient's health and function, and social determinants of health. However, relatively little work has been done in the literature on formal development of models that describe the likely patterns of drug usage which increase the risk of readmission. Recent developments in analyzing big data by Microsoft researchers has allowed a decision support system, Amalga, to analyze $25,000$ clinical and administrative variables and predict hospital patients' readmission risk score in an applied machine learning setting in the Greater Washington, DC, Metropolitan area (Horvitz 2010). There is still no evidence in the literature on validation of this system and its performance for clinical purposes. However, the access to clinical data such as vital signs, lab results or information related to the physicians in charge is not easy to obtain for general health services analysis.

Most models created to date for hospital comparison or clinical purposes have poor predictive ability which prevents their generalization (Kind 2007; Wolff 2002; Pham 2007). The area under the ROC curve for performance reported using retrospective administrative data in the studies reviewed in the literature are in range of 0.61 to 0.63 (Kansagara et al. 2011). Developing richer models would require insights about the causality of readmission and mechanisms of provided care.

Supervised Learning Approach

We approached readmission prediction as a supervised learning task. Building on the analysis of readmission in the literature, we use patients demographics, history of readmissions, procedure codes related to medical or surgical procedures performed during the hospital stay, diagnostic codes that indicate the leading disease and comorbidities in the patient, in addition to prescription drugs with drug classification codes at the aggregate level to discover the risk of readmission for each hospital admission record. Hospital admission record is considered as the unit of analysis. We treat hospital admission records as a set of parameter values, which must be classified as either positive or negative examples leading to future readmissions.

As we used administrative data from the hospital systems, there is a gold standard for each patient over the age of the cohort that identifies whether or not each patient readmitted following a discharge. Therefore, we can label the data perfectly and frame the problem as a classical machine learning problem of learning from examples. We examined a classification methods from the category of generative classifiers, a Naive Bayes classifier, and one from the category of discriminative classifiers, a decision tree classifier. The motivation for the choice of algorithms is the fact that both Bayesian methods and decision trees allow us to visualize which features are important in the prediction of readmission ensuring that domain experts can interpret the results in the context of their existing knowledge.

Preprocessing

Feature selection as an active field of research in the high-dimensional data analysis offers a variety of different methods for reducing the dimensionality of the data. No consensus exists on how to distinguish among broad range of feature reduction methods the ones that fit our problem the best. However, the interpretability of the results are important in our application. Therefore, we cannot use dimensionality reduction techniques such as principal component analysis or its variations for this problem. Therefore, in this paper we used statistical methods from information-based and frequency-based approaches in the literature to reduce the number of features. Both methods take as input a matrix of admission records data for two feature categories: patient demographics and codes related to drug-diagnosis-procedure and return a small set of features from drug-diagnosis-procedure category attached to the corresponding demographic features.

From the class of information-based feature reduction methods, we used *Gini indexing* which is a standard measure of statistical dispersion with the value between zero and one. Gini index is commonly used in economics as a measure of inequality of income (the higher this indicator is above 0, the higher the inequality). In the context of our application, the value of 0 for a feature shows that all the members in the dataset belong to the same class and therefore we can get the maximum useful information from this feature, when the value of one shows that the samples in the data are distributed equally over the class and we can not gain much information from this feature. The second statistical feature selection method is frequency-based feature selection , that is, selecting the features that are most common in the class. This method is meant for reducing the dimensionality of hospital admission dataset based on ranking frequency counts for each drug-diagnosis-procedure feature. We are also interested to investigate the effect of natural grouping of features based on medical taxonomies of drugs, procedures, and diagnosis on the classification performance. We refer to this approach as domain-knowledge-based method. There exist a variety of conceptual level medical classification for medications, for international classification of diseases,$ICD9$, diagnostic codes and for medical-surgical procedure codes that provides a method to systematically categorize the codes falling into these attributes. A conceptual medical classification system represents an internationally standard way to describe and compare medical utilization data. In our analysis for this paper, we used American Hospital Formulary Service, *AHFS*, classification system for pharmaceutical codes. The $AHFS$ Pharmacologic-Therapeutic Classification was developed and is maintained by the American Society of Health-System Pharmacists (ASHP). For the procedural codes we used *Chapter*, the Canadian Classification of Diagnostic, Therapeutic, and Surgical Procedures. We used $ICD9$ diagnostic codes and grouped them into the comorbidities described by Elixhauser.

Identification of hard-to-predict cases

Like any classification problem, there are easy to predict and hard to predict cases in analysis of readmission prediction. One of our objectives in this research is to identify particularly the readmission records that are hard to detect at the discharge point of the initial admission. We hypothesize that the readmission cases in the data that are always missed when we use different classifiers and different feature spaces should account for these hard-to-predict cases. These difficult cases could imply that either there are some confounding factors that we have not measured in any of our models or they are outliers. Whether or not the hard-to-predict cases account for unavoidable readmissions is not in the scope of this research. However, further analysis of these cases and possible characterization of their attributes is in the area of our future explorations. Naturally, the cleaned dataset after removing the potential outliers should improve the readmission prediction performance. In our experimental results we observe how much the performance of each classifier improves by doing such.

Hospital Discharge Data Set

We used a large cohort extracted from the Quebec administrative database of hospitalization information, obtained from the *Regie de l'assurance maladie du Quebec* (RAMQ). We enrolled patients into this cohort after their first diagnosis of a respiratory illness between January 1st, 1996 and December 31, 2006 while living in in the census metropolitan area of Montreal, as defined by the 2006 Canadian census.

These data provide complete information on age, sex, census tract of residence, hospital procedures that results in 2733 procedure-related features, hospital diagnostic codes that results in 3738 diagnosis-related features, outpatient physician visits, outpatient diagnostic codes, and emergency department visits. Since Quebec provides universal provincial drug coverage for people 65 years or older, these data include all drug prescriptions for these people. This results in 5920 features related to the drugs. Planned hospital admissions have a special code to distinguish them from unplanned admissions. All patient, physician, hospital and clinic names were anonymized. For patients, the birth-month was available, but not the birthday.Our data set include all Quebec healthcare utilization data for all included patients after enrolment, even if they moved to another Quebec location. Therefore, hospitalizations outside of Montreal were included. Since these data do not include the hospital name or location, we could not distinguish between Montreal hospitals and other Quebec hospitals. We examined discharges

Table 1: Distribution of prescription drugs among patients with versus without readmission record in 30 days after discharge.

AHFS Class	#Not readmitted (%)	#Readmitted (%)
Anti-infective Agents	59668 (2.2%)	12295 (2.3%)
Antineoplastic Agents	13824 (0.5%)	2569 (0.5%)
Autonomic Drugs	156605 (5.7%)	38808 (7.1%)
Blood Formation, Coagulation, and Thrombosis Agents	103769 (3.8%)	23818(4.4%)
Cardiovascular Drugs	790439 (28.7%)	145851 (26.8%)
Central Nervous System Agents	579941 (21%)	109657 (20.2%)
Electrolytic, Caloric, and Water Balance	293973 (10.7%)	60994 (11.2%)
Eye, Ear, Nose, and Throat (EENT) Preparations	58968 (2.1%)	10093 (1.9%)
Gastrointestinal Drugs	158813 (5.8%)	33174 (6.1%)
Hormones and Synthetic Substitutes	281209 (10.2%)	53604 (9.9%)
Miscellaneous Therapeutic Agents	74350 (2.7%)	13645 (2.5%)
Respiratory Tract Agents	8002 (0.3%)	2114 (0.4%)
Skin and Mucous Membrane Agents	24893 (0.9%)	4721 (0.9%)
Smooth Muscle Relaxants	21421 (0.8%)	4826 (0.9%)
Vitamins	70253 (2.5%)	12836 (2.4%)

from the twenty hospitals with the most discharges (of patients 65 years or older), which are almost certainly Montreal hospitals.

In this research, we included all discharges from the twenty hospitals described above for all enrolled patients who were 65 years of age or older at the time of discharge. In these data, 619,274 hospital discharges met these criteria. In order to have a sense of the distribution of prescription medications among patients with positive and negative readmission record, Table 1 present some descriptive statistics on our dataset that compares prescription medication at the time of admission between those who were eventually readmitted and those who were not. The dataset in our study poses analytical challenges for machine learning methods with respect to dimensionality of the data records. As we explained in the previous section, there are more than twenty thousands of features related to the diagnostic codes, drug utilization codes, and procedure codes plus the demographics of the patients. This makes the dataset very large and sparse. While we do not anticipate that all of these attributes are distinct predictors of readmission, there is not sufficient evidence, however, to determine factors that might be important and those that might not. Therefore, we applied a pre-processing step using feature reduction techniques in order to make it computationally easier for the classifiers.

Empirical Results

In measuring the prediction performance, we ran a large number of experiments using the rapidminer software (Mierswa et al. 2006). Each experiment assigned a different learning algorithm and a different feature selection technique to the dataset described earlier in this paper. We applied down-sampling of the negative class (not readmitted), by random sampling 31.48% of the negative class. The reason for this is a class imbalance problem with our data. For the case of decision tree classifier , we optimized the tree based on different combinations of maximum depth and minimum split size. The training portion of the dataset (provided by cross validation) was divided to 10% and 90% of samples. The down sampling was applied on the training set (90% of samples) and the test set was left unchanged in order to keep the same distribution of class labels as the original data. Table 2 summarizes the results of our prediction performance assessment obtained by different feature selection methods and different classifiers. The first two columns of this table shows the mean accuracies area under the ROC curve, AUC, over the datasets as reached by the different combinations in 10-fold cross-validation for Naive bayes and decision tree classifiers. The effect of domain knowledge feature reduction on the classification performance was investigated and presented in the last row of this table. The conceptual grouping of medical classifications for drug codes, diagnostic codes, and procedure codes results in the total number of 63 features. For the purpose of a fair comparison between all feature selection methods, in this set of experiments we have selected the same number of features from the top gini index and frequency rank. We generally observe only limited differences between the feature selection method of gini indexing, frequency ranking and domain-knowledge-based grouping when the same number of features are selected. We also observed that between the two classification algorithms, there is no winner as both classifiers perform similarly.

Although the performance of the Naive Bayes classifiers and the decision tree classifiers in our experiments were not significantly different, we still used both classifiers in experimental settings with a range of dimensionsionalities with respect to both gini indexing and frequency ranking, as well as the domain-knowledge-based approach for feature selection to gain some insights about the hard-to predict readmission cases (outliers). This includes 21 different experimental settings. We identified the readmitted records which are missed by all these 21 classification experiments as outliers. This includes only 6% of the entire dataset. We examined the performance of Naive Bayes classifiers after removing the hard-to-predict cases from the dataset. These results are presented in the third column of Table 2. Some descriptive statistics on the original dataset and the hard-to-predict cases (outliers) are presented in Table 3. These features are cho-

Table 2: Performance of readmission detection algorithms in terms of area under the ROC curve.

Feature Reduction	Naive Bayes	Decision Tree	Outliers Cleared
Gini Indexing	0.65	0.64	0.84
Frequency Ranking	0.67	0.67	0.83
Domain-Knowledge-Based	0.65	0.63	0.82

Table 3: Descriptive statistics of the hospital admission dataset in Montreal, QC

Feature	Not readmitted (n=534,869)	Readmitted (n=84,405)	Outliers
Gender-Male	47%	49%	48%
Age	76.7 years	77.0 years	76.7 years
Emergency admission	81%	91%	83%
Length of stay	13.9 days	14.3 days	13.6 days
Previous readmissions	0.40	0.94	1.24

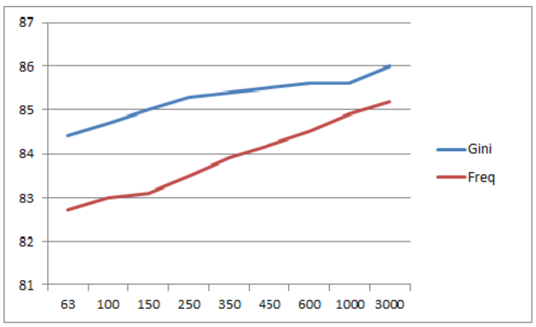

Figure 1: Performance comparison between two statistical feature selection methods in terms of area under the ROC curve, AUC, of prediction of readmission applied on hospital admission dataset.

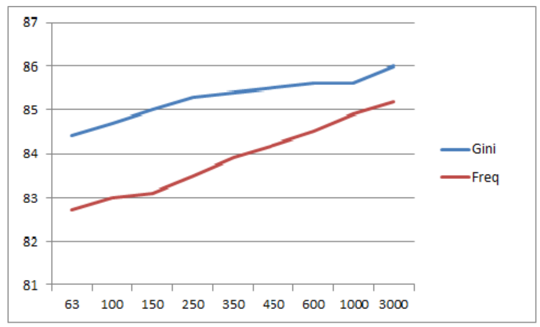

Figure 2: Performance comparison between two statistical feature selection methods in terms of area under the ROC curve, AUC, of prediction of readmission applied on hospital admission dataset after removing outliers.

sen based on their popularity in the literature for being a predictor of hospital readmission. These results show that there is a somewhat significant difference between the general readmitted group and outliers in several variables including emergency admission, length of stay, and previous readmissions. For some variables, the outlier group are similar to not readmitted group, including length of stay and emergency admission. We intend to extend our analysis further on this group of patients.

So far, we studied a limited number of features selected according to Gini index value and frequency ranking. We will now investigate the impact of increasing the number of features on the prediction performance. Figure 1 shows the result of this experiment on the original data set, and Figure 2 shows the results of the same experiment obtained after removing the outliers. As can be seen, the performance of frequency-based feature selection is higher than that of Gini index on the entire data set (Figure 1). However, the Gini index outperforms the frequency-based feature selection on the dataset after removing the outliers (Figure 2). Overall, the most significant effect on the results is given by the dataset used, and not by the feature selection method. This means that modeling efforts in the area of readmission prediction should be more focused on characterizing the types of patients and acquiring knowledge about the mechanisms that cause different types of readmissions.

Conclusion and future work

The cost of readmission is a huge burden on health systems as well as patients. There is currently a critical need for methods that can increase our understanding of what is important in risk of readmission. In this paper, we used machine learning methods for supervised classification to predict hospital readmission within thirty days of hospital discharge, using a very large dataset from Quebec. Our results suggest that prescription medications, diagnostic information and information on procedures during hospital admission can successfully predict hospital readmission. Our findings suggest that medical taxonomies that provide conceptual grouping for pharmacological, diagnostic, and procedural codes can be used as a way of dimensionality reduction in order to overcome the computational burden of dealing with very large numbers of infrequent features.In our results, there is no significant performance loss using this approach compared to statistical methods for feature selection, when the number of features considered by the two types of methods is the same. Our early results in the area of identifying readmission outliers confirm that all readmission records should not be treated equally.

The findings of this study provide critical input for efforts to improve prediction models for readmission and more importantly to identify opportunities to enhance clinical care pathways in order to prevent readmission. In terms of prediction, we have shown that existing medical terminologies can be used to reduce the number of predictors without adversely affecting prediction accuracy. The finding that patients can be segmented in groups that are harder and easier to predict has implications for both prediction modeling and clinical care. In terms of prediction modeling, it suggests that there may be value in segmenting patients and then optimizing prediction strategies for different subpopulations. From a clinical care perspective, identification of patient populations for which readmission risk is difficult (or easy) can provide important insight into how variations in clinical care can influence readmission.

The results presented are intended for several different populations of users. Clinicians and hospital administrators should be able to use this information, especially the features which are most predictive of readmission and the types of "outliers" we identified, in their efforts to improve the quality of care and prevent readmissions. At the same time, these results can be useful to insurance companies, for patient-level risk assessment and future hospitalization cost estimation. Finally, health services assessment agencies can use this type of tool for provider-level performance assessment, a very hot topic in current health care administration. While the statistics we present are already useful as-is, deploying this type of predictor in a "live" setting would require building software that interfaces directly with the health network's electronic records. In Quebec, given the centralized nature of the health system, this is not difficult, and we are currently exploring this possibility. Looking more broadly at North America, the push towards electronic record systems make this type of software development possible, albeit more challenging if the types of information needed are in a more heterogeneous format at different sites.

In the future, we plan to extend this research by using additional feature reduction algorithms and running additional experimental studies. Consensus has not yet been reached as to the time frame that should be used in defining a readmission; therefore we will investigate shorter and longer readmission time frames as a criteria in future experiments. Future studies should also identify and assess different types of patients from the point of view of readmission, as well as the causality for readmission.

References

Amarasingham, R.; Moore, B.; and Tabak, Y. 2010. An automated model to identify heart failure patients at risk for 30-day readmission or death using electronic medical record data. *Med Care* 48(11):981–988.

Benbassat, J., and Taragin, M. 2000. Hospital readmissions as a measure of quality of health careadvantages and limitations. *Arch Intern Med* 160(8):1074–1081.

Billings, J.; Mijanovich, T.; and Wennberg, D. 2006. Case finding for patients at risk of readmission to hospital: development of algorithm to identify high risk patients. *BMJ* 333(7563):327.

Canadian Institute for Health Information. 2012. All-cause readmission to acute care and return to the emergency department. *CIHI* 10.

Catlin, A. 2008. National health spending in 2006: A year of change for prescription drugs. *Health Affairs* 27(1):14–29.

Cotter, P.; Bhalla, V.; Wallis, S.; and Biram, V. 2012. Predicting readmissions. poor performance of the lace index in an older uk population. *Age and Ageing* 41(6):784–789.

Gruneir, A.; Dhalla, I.; Walraven, C.; Fischerand, H.; and Rochon, P. 2011. Unplanned readmissions after hospital discharge among patients identified as being at high risk for readmission using a validated predictive algorithm. *Open Med* 5(2):31.

Halfon, P.; Eggli, Y.; Pretre-Rohrbach, I.; Meylan, D.; and Burnand, B. 2006. Validation of the potentially avoidable hospital readmission rate as a routine indicator of the quality of hospital care. *Med Care* 44(11):972–981.

Hammill, B.; Curtis, L.; and Fonarow, G. 2011. Incremental value of clinical data beyond claims data in predicting 30-day outcomes after heart failure hospitalization. *Circulation: Cardiovascular Quality and Outcomes* 4(1):60–67.

Heggestad, T., and Lilleeng, S. 2003. Measuring readmissions focus on the time factor. *International Journal for Quality in Health Care Volume* 15(2):147–154.

Hernandez, A.; Greiner, M.; and Fonarow, G. 2010. Relationship between early physician follow-up and 30-day readmission among medicare beneficiaries hospitalized for heart failure. *JAMA* 303(17):1716–1722.

Horvitz, E. 2010. From data to predictions and decisions. enabling evidence-based healthcare. *Series on Data Analytics. Computing Community Consortium*. Microsoft Research Redmond.

Kansagara, D.; Englander, H.; Salanitro, A.; Kagen, D.; Theobald, C.; Freeman, M.; and Kripalani, S. 2011. Risk prediction models for hospital readmission: A systematic review. *JAMA* 306:1688–1698.

Kind, A. 2007. Bouncing back: Patterns and predictors of complicated transitions thirty days after hospitalizations for acute ischemic stroke. *Journal of the American Geriatrics Society* 55(3):365–373.

Krumholz, H.; Normand, S.; and Keenan, P. 2008a. Hospital 30-day acute myocardial infarction readmission measure: Methodology. *Report prepared for Centers for Medicare and Medicaid Services*.

Krumholz, H.; Normand, S.; and Keenan, P. 2008b. Hospital 30-day heart failure readmission measure: Methodology. *Report prepared for Centers for Medicare and Medicaid Services*.

Krumholz, H.; Normand, S.; and Keenan, P. 2008c. Hospital 30-day pneumonia readmission risk measure: Methodology. *Report prepared for Centers for Medicare and Medicaid Services*.

Mierswa, I.; Wurst, M.; Klinkenberg, R.; Scholz, M.; and Euler, T. 2006. Yale: Rapid prototyping for complex data mining tasks. In *KDD '06: Proceedings of the 12th ACM SIGKDD*, 935–940.

Morrissey, E.; McElnay, J.; Scott, M.; and McConnell, B. 2003. Influence of drugs, demographics and medical history on hospital readmission of elderly patients: A predictive model. *Clinical Drug Investigation* 23(2):119–128.

Pham, J. 2007. Care patterns in medicare and their implications for pay for performance. *New England Journal of Medicine* 356(11):1130–9.

Stone, J., and Hoffman, G. 2010. Medicare hospital readmissions. issues,policy options and ppaca. *Congressional Research Service Report for Congress*.

Suissa, S.; Ernst, P.; and Kezouh, A. 2002. Regular use of inhaled corticosteroids and the long term prevention of hospitalisation for asthma. *Thorax* 57(10):880–884.

Walraven, C.; Dhalla, I.; Bell, C.; Etchells, E.; Zarnke, K.; Austin, P.; and Forster, A. 2010. Derivation and validation of an index to predict early death or unplanned readmission after discharge from hospital to the community. *CMAI* 6(182):551–557.

Wolff, J. 2002. Prevalence, expenditures, and complications of multiple chronic conditions in the elderly. *Archives of Internal Medicine* 162(20):2269–76.