USING PREDICTION TO IMPROVE PATIENT FLOW IN A HEALTH CARE DELIVERY CHAIN

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Abstract

Often, in a health care delivery chain, lack of coordination has been detrimental to timely, high quality care. This paper focuses on the two steps of the hospital health care delivery chain, an emergency department and a hospital's inpatient units. Past research into this chain has suggested that early prediction of patient need for admission can be used to better align flow between the two departments. This chain and the nature of prediction in health care delivery are discussed as well as a how prediction may be useful in this context. Finally tools for making admission predictions are tested and their possible implications are explored. The results of this exploration show that both expert opinion and a Naïve Bayesian statistical approach have predictive value in this context.

Introduction

Fragmentation is often suggested as a major driver of cost in the United States health care system [Lee & Mongan 2009]. A health care delivery chain is a series of treatment steps through which patients flow. In such chains operational inefficiencies can be made visible by excess waiting times. When patients are waiting for access to the next step in the chain, this is similar to excess inventory in manufacturing systems [Goldratt & Cox 1989, Hopp & Spearman 2001]. However in health care, the costs of this "inventory" buffer goes beyond storage costs, it also can have significant impact on the quality of care that a patient receives. This paper focuses on the hospital emergency department (ED)/inpatient unit (IU) chain; it discusses flow through this chain and develops a prediction model for generating demand predictions to be used in the ED/IU chain, as they are often used to manage manufacturing and supply chains.

The Emergency Department - Inpatient Unit System

From high level view, when a patient enters the ED, they are often greeted and quickly looked over for anything needing immediate attention. Then the patient is seen by a nurse in triage where basic information and tests are performed and the patient is assigned a priority level. The patient then waits to be given a bed in the ED. At the end of their treatment it is decided whether the patient needs to be admitted to the hospital or discharged.

In the emergency environment many metrics of quality are defined by how quickly a patient gets to and through required treatment [Graff et al. 2002, Bernstein et al. 2009, Horwitz et al. 2010].

Early solutions to ED flow were summarized as increased resources, deferral of low risk patients, and new technologies [Forster 2005]. It is now understood that the interface between the ED and where patients flow out of the ED, the IU, is "the single most important factor" [Olshaker & Rathlev 2006] attributed to flow problems experienced by the ED [US GAO 2003, 2009].

Prediction in Health Care

In response to the limitations of current solutions to improve flow between the ED and IU, recent literature has suggested that if IU admission could be predicted and communicated to the rest of the hospital when a patient enters the ED, then the IU could begin preparations before the patient has completed emergency treatment, reducing waiting time between steps [Yen & Gorelick 2007].

Prediction is a fundamental aspect of how management science improves the efficiency and effectiveness of enterprises. However, it has not been used to its full potential in health care. In-fact the use of prediction to allow proactive care has been listed as one of the fundamental elements of redesigning the health care system laid out by the Institute of Medicine [IOM 2001].

It is natural for a practitioner to feel a little discomfort with the idea of using prediction. There is a great deal of uncertainty in health treatment. A doctor makes a diagnosis and treatment decision based on the best information that they could acquire, however 100% confidence is rarely, if ever, achieved. It is only natural for people in an environment of such uncertainty to desire moments of absolutism. For example, it is absolutely true that a patient will be admitted to an IU from an ED, when the ED doctor makes the admit decision. This has an appeal to those operating in the system, because it means they can act on firm decisions. However waiting for the concrete decision, though comfortable, is not necessarily best for flow; it allows the bottleneck between the ED and IU to become significant. On the other hand by introducing some uncertainty it is possible to improve flow and productivity. Looking at a simple inventory model, it is possible to wait until customers order a product before beginning production, however that means long waits. To solve this, prediction can be used to guess product demand, begin production early and satisfy customers in a timely manner. This has the drawback of possibly having too much or too little inventory. However a vendor is comfortable with introducing uncertainty and many methods have been developed to avoid over or under stocking; such is not necessarily the case in health care delivery.

Some studies have approached the idea of predicting admission from the ED to the IU. Many of these articles are focused on specific diseases and associated indicators of admission such as patients with coronary syndromes [Arslanian-Engoren 2004], patients with abdominal pain [Sadeghi et al. 2006], and pediatric patients with bronchitis [Walsh et al. 2004]. It was even studied whether paramedics and other emergency medical staff can predict admission while on route to a hospital [Levine et al. 2006, Clesham et al. 2008]. One article was found that made predictions for an entire ED population using a Bayesian Network [Leegon et al. 2005].

The rest of this paper will be dedicated to exploring methods for predicting admission from the ED to the IU. This exploration will be done with a practical eye towards applying the prediction.

Prediction Experiment

The following section describes multiple methods for predicting whether a patient will be admitted to the IU from the ED and the results of applying this method.

Expert Opinion

When considering options for predicting whether a patient will require admission or not, the first obvious prediction method to try is expert opinion. A likely step in the ED treatment process to do a prediction of admission need is at triage. This is because it is at triage that many properties of the patient are assigned which makes those nurses who perform triage used to looking at the patient and making quick categorizations. Another significant benefit of doing the prediction at triage is that it is early in the process. This is also the first time within the ED/IU chain that a patient is seen by an expert. The intuition behind making a prediction as early as possible is that this gives more time for the system to react to the predicted information. However there is an inherent tradeoff between how early a prediction is made and how accurate it will be. The likelihood of a patient being admitted will continually become more and more clear right up to the point that the emergency physician makes the final call to admit the patient. However as that point approaches the prediction becomes less useful.

The Veteran's Health Administration Hospital at West Roxbury, MA ran a quality improvement project that explored the ability of a triage nurse to predict whether a patient will need admission to the IU. For every new patient in triage the nurse is given a brief form to complete. This form included a space at the top to include the patient identification label and the question:

"How likely is it that the patient will need admission to the hospital?

- □ Definitely Yes (95-100%),
- □ Highly Likely (75-94%),
- □ Likely (50-74%),
- □ Unlikely (25-49%),
- □ Highly Unlikely (5-24%),
- □ Definitely No (0-4%)."

This format introduced an aspect of prediction that had not been explored in the other studies that the authors had found. In this case the question was not simply seeking a yes or no answer but instead was seeking a range of possibility, which is more realistic and allows for the development of more complex systematic responses.

The prediction was performed for 1 month generating 641 patient data points. Figure 1 shows the results of nurse predictions for patient admission. For each category of prediction the percentage of patients that were admitted and not admitted is shown. There is also a category for patients who skipped triage because the medical staff felt it was important to get the patient into treatment without any delay (no prediction was made for these patients).

As can be seen, nurses are certainly able to stratify patients by likelihood of admission. The results show the actual proportion of patients admitted rises in concert with the prediction category. However, it can be noted that the admission percentages in each category do not match the suggested percentages that were given in the form. Nevertheless these predictions are certainly better than the simple percentage prediction shown by the two dashed lines. These lines represent the fact that ~30% of patients from this ED get admitted to the hospital.

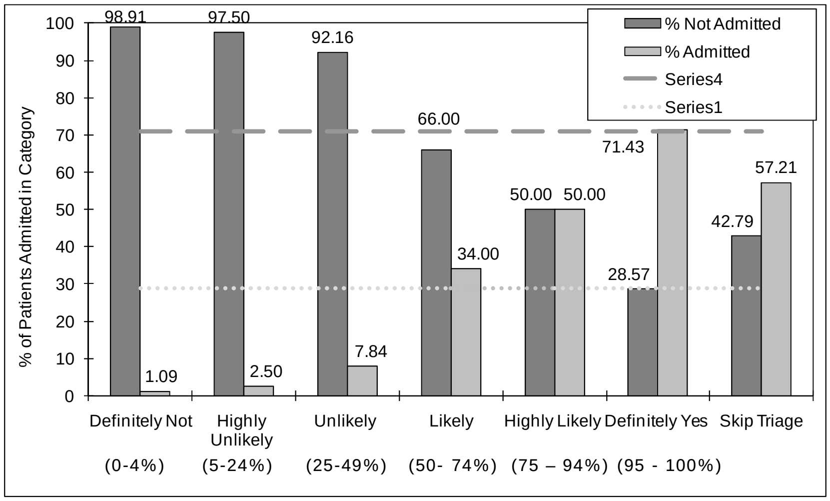

Figure 1 Nurse Prediction of Patient Admission vs Percent of Patients Who Actually Do or Do Not Get Admitted

Statistical predictions

There are many different methods that have been employed in order to make predictions in health care. Some of these methods require an in depth knowledge of statistics and high level understanding of machine learning tools and software. However in a typical ED setting such tools and knowledge may not be available. It is interesting in that case to consider a less complicated statistical prediction tool, Naïve Bayes.

The Naïve Bayesian approach uses the simplifying assumption that all factors are independent. However despite the fact that a complicated system such as the ED will inherently have some interdependence of factors the Naïve Bayesian approach has been shown to be practical given large data sets [Witten & Frank 2005, Shmueli et al. 2007].

To apply this method data was collected from the VHA Boston Emergency Department database. The data for 1/1/2010-5/6/2010 was extracted consisting of 4200 independent ED visits. Each data point included the following factors for the Naïve Bayes predictor:

- Discharge: Admit, Not admit
- Age: continuous
- Arrival Method: Stretcher, Wheelchair, Ambulatory
- Acuity Level: Non-Emergent, Emergent, Urgent
- ED designation: Emergency Room, Fast-Track
- Primary Complaint: Free Language

When using the Naïve Bayes technique, all factors must be categorical, so age was broken up by decades as described above. However primary complaint was not as readily categorized. Primary complaint was noted in the data set using free text, meaning either exactly what the patient said or the nurse's interpretation of that statement. This means possible spelling errors as well as a lack of consistency in notation. Table 1 lists all of the complaint codes that were generated in order to use primary complaint as a predicting factor. These codes were manually applied to each of the 4200 points in the training set and then applied to each of the 641 experimental points.

With categories set for each of the training and experimental points, it was possible to apply the Naïve Baysian equation using combinations of each of the available factors. For example:

- Complaint alone,
- Complaint and Age,
- Complaint, Arrival Mode, and Age
- Arrival Mode, Age, and ED Designation

For each of the different combinations, a probability of admission was generated for each point in the experimental set. Based on the probability of admission assigned to each patient they were assigned to the categories of admission from above (Definitely Not 0-4%, Highly Unlikely 5-24%, etc.). Then for each category it was calculated how many patients were actually admitted. Using the combination of Primary Complaint, Arrival Mode, and Age provided the best fit to the categories with an admission percentage as seen in Figure 2. From this point on, this prediction will be called "VA Bayes."

The results of the predictions that have been provided above are in probability groups as opposed to making a prediction of a binary yes or no. This is a distinct difference from all similar studies that the authors located. The importance of this distinction will be discussed in the next section. However in order to enable comparison between this study and the studies in the literature it is possible to simply specify that a probability of admission >50% means a yes-admit prediction and <50% is a no-admit prediction. In this way, it is possible to establish the standard prediction parameters of positive predictive value, negative predictive value, sensitivity and specificity. These parameters are tabulated below (Table 2) for each of the methods employed in this study as well as the values achieved by past studies.

Table 1 Complaint Codes

Abdominal Pain	Cellulitis	Fever	Lethargy	Rash
Abnormal Labs	Chest Pain	Flu	Liver Failure	Renal Failure
Abscess	Cold	Foley	Lump	Sciatica
Allergy	Cut	Foreign Body	Mental	Seizure
Anemia	Cyst	Gastrointestinal Problem	Motor Vehicle Accident	Shortness of Breath
Appendicitis	Dehydration	Gout	Nausea / Vomiting	Sexually Transmitted Disease
Ascites	Dental	Headache	Neck Pain	Stroke
Ataxia	Detox	Health Maintenance	Nose Bleed	Surgery Eval
Back Pain	Difficulty Swallowing	Hematoma	Orthopedic	Swelling
Bites and Stings	Dizziness	Hematuria	Other	Syncope
Bleeding	Deep vein thrombosis	Hemoptysis	Other Circulatory	Ulcer
Blocked Insert	Ear	Hernia	Other Numbness	Urinary Retention
Blood Pressure	Edema	Hyperkalemia	Other Pain	Urinary Tract Infection
Blood Sugar	Emphysema	Hyponatremia	Other Respiratory	Vision
Bronchitis	Exposure	Hypoxia	Other Skin	Weakness
Burn	Eye	Infection	Pancreatitis	White Blood Cell Count
Cardiac	Fall	Kidney Stone	Pneumonia	Wound

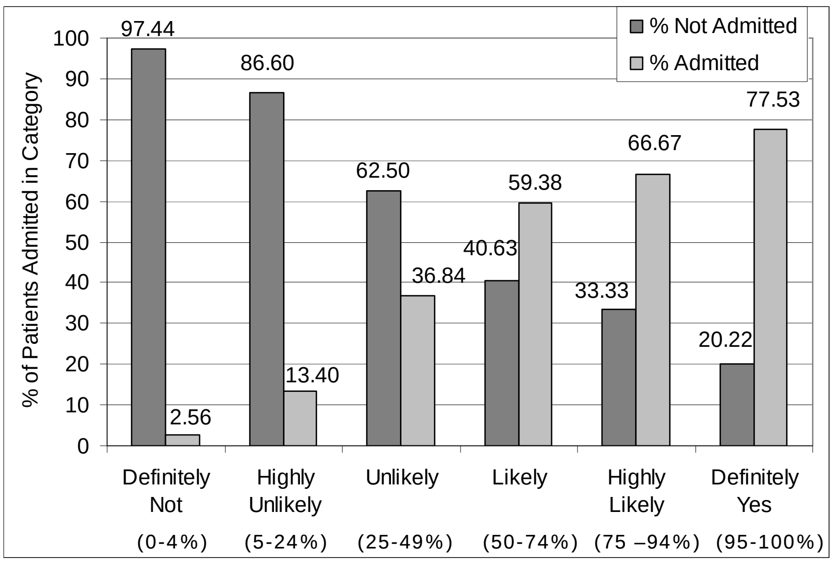

Figure 2 Statistical Predictions of Patient Admission vs Percent of Patients Who Actually Do or Do Not Get Admitted

Table 2 Results

	Method	Sensitivity	Specificity	Positive Predictive Value	Negative Predictive Value
VA Test	Expert - Triage	55.66	86.98	48.11	97.45
VA Bayes	Naïve Bayes	53.48	91.41	71.94	82.67
Leegon 2005	Bayesian Network	90	71	56	95
Arslanian-Engoren 2004	Expert - Triage	57	59	68	56
Clesham 2008	Expert - EMS	71.7	77		
Levine 2006	Expert - EMS	62		59	
Walsh 2004	Neural Netowork	78	82	68	89
Sadeghi 2006	Expert - Triage	64	48	52	61
	Bayesian Network	90	25	51	75

Discussion and Future Work

Predictions can be made using many methods; the two that were shown are expert opinion and Naïve Bayes. Both showed great predictive potential. With this said, it is worthwhile looking at the nature of the data that was generated during this study. When it was suggested that the methods employed have predictive value, it was meant that a prediction of percent likelihood of admission has some correlation to the actual percent of admission in patients grouped into a specific category. In that way it is possible to develop a tool as in VA Bayes, that will provide a prediction of admission likelihood and it is possible to take that prediction and make operational decisions. If the tool says the patient is highly unlikely to be admitted a hospital bed manager can be told that there is a 13.4% chance that the patient will need admission and the manager can make decisions with that in mind.

This is a different approach than the diagnosis mindset which leads to measures such as sensitivity and specificity that were adopted in other studies. It is wishful thinking in such a complex system to believe that we can develop a tool that will provide an accurate yes or no answer. However in the medical field where tests are developed in order to decide if a patient does or does not have an illness it is natural to term health care delivery chain studies using the same metrics. Indeed, a more probabilistic approach may be of limited use on an individual patient level however it may be very useful when applied to aggregates of patients moving through the ED.

Looking at Table 2, it can be seen that based on the standard ways of measuring the success of a predictor VA Bayes does not actually perform the best. However, when looking at it broken by admission likelihood category it can be seen as a much more dependable tool. Given that both expert opinion and the Naïve Bayes have predictive value; when thinking about actual implementation one must ask about the reality of workflow in the ED environment and whether a computer based predictor can actually be installed no matter how simple it is. It is also important to think about how the information will be used on the inpatient side. Naturally the more accurate the prediction the more useful the information, so it must be understood through future studies how the information will actually be used and therefore how much of a trade off in productivity comes from the relaxation of predictive accuracy.

Conclusion

A health care delivery chain is one in which patients flow through multiple steps of a treatment process. Often the fragmentation between two steps leads to inefficiencies, high costs, and reduced quality. One such two-step chain is the Emergency Department and Inpatient Unit of a hospital. It is suggested that this problem can be improved by tying demand for the emergency department directly to demand for the inpatient unit through prediction. However the practical implications of such a concept require significant research into medical decision processes, culture and technical capability. The ability to make predictions of a patient's likelihood of admission from the ED to the hospital was studied using expert opinion and statistical methods. It was shown that both methods have predictive value. Finally the implications of the data and its format were discussed in terms of how it can be practically used in a functional health care delivery chain.

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