Optimization of Intervention Strategies for Reducing Hospital Readmissions

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Abstract

An upcoming change to hospital reimbursements from the Centers for Medicare and Medicaid Services (CMS) has placed pressure on hospital systems to reduce the rate of avoidable readmissions. One of the main methods which hospital systems are able to employ to reduce these rates is enacting targeted interventions on specific patient diagnosis groups. Of primary interest is Congestive Heart Failure (CHF), which often accounts for the largest percentage of hospital readmissions. When a hospital system is defining the strategy for reducing readmissions, there is a difficulty in selecting the proper mix of interventions. We present a method which allows the selection of proper interventions, in conjunction with defining the group for which those interventions should be enacted upon. The method for solution utilizes an integer programming approach with constraints from a financial framework to estimate the impact as well as the expectation of results from intervention strategies.

Keywords
Optimization, Genetic Algorithm, Hospital Readmissions, Readmission Prevention

1. Introduction

At present, it is estimated that 75% of healthcare expenditures are focused on the treatment of chronic diseases.[1,2] A chronic disease, is one for which there is no known cure, which patients will have for the rest of their lives. While these conditions may be managed, reducing or eliminating the side-effects of the disease, there is no cure. There are several factors at work which have lead to this. An aging population, improvements in healthcare which can now prevent mortality in situations which would have previously been terminal, improved chronic disease management programs which lower the mortality risk of patients, and many other additional factors. Whatever the reasons for this trend, our concern is what actions a hospital system can undertake to reduce their readmission rates while maintaining cost-effective outcomes.

Having a growing proportion of the patient population living with one or more chronic disease has a large effect on the healthcare system. One of the largest impacts deals with readmission rates. When a patient enters the hospital as an inpatient they are considered ‘admitted’ to the hospital. Once the patients’ treatment has completed, and they are stable, the patient is discharged. At this point, the goal is that the patient is no longer requiring hospital inpatient services, and should not require them for an extended period of time. One metric for the quality of care that a hospital is providing is the ‘readmission rate’. A readmission occurs when the patient is once again admitted to the hospital after they have been discharged. Typically, the length of time which is of interest is 30 days. A patient admitted to the hospital within 30 days of their latest discharge is considered a readmission. However we should note that there are a variety of lengths which are often tracked, such as 7, 15, 60, 90, 365. This is considered to be a measure of delivering quality care, as patients who are treated effectively would be less likely to require hospital services recent to a discharge. This also eliminates of a conflict of interest, whereby a hospital system would have an incentive to deliver poor care as that would generate additional patient volume from repeated admissions from patients.
The importance of this issue has been magnified recently due to an addition of section 1886(q) to the Social Security Act, as part of the Affordable Care Act.[3] This act establishes several things. Hospitals with disproportionately high readmissions will face reductions in reimbursements. It does this by viewing the readmissions for patients in the Diagnosis-Related Group (DRG) of Acute Myocardial Infarction (AMI), Heart Failure (HF) and Pneumonia (PN) and determining the excess readmission ratio, a calculation based on a national average and adjusting per the hospitals patient population, including aspects such as comorbidities, frailty, and demographic characteristics. In future, the conditions being targeted are likely to be expanded to include acute exacerbation of chronic obstructive pulmonary disease (COPD); and (2) patients admitted for elective total hip arthroplasty (THA) and total knee arthroplasty (TKA). The specific definitions for calculations are as such.[4]

Formulas to Calculate the Readmission Adjustment Factor

\[
Excess\ readmission\ ratio = \frac{\text{risk adjusted predicted readmissions}}{\text{risk adjusted expected readmissions}}
\] (1)

\[
Aggregate\ payments\ for\ excess\ readmissions = \left( \text{excess readmit ratio for AMI} - 1 \right) \sum \text{base operating DRG payments for AMI} \\
+ \left( \text{excess readmit ratio for HF} - 1 \right) \sum \text{base operating DRG payments for HF} \\
+ \left( \text{excess readmit ratio for PN} - 1 \right) \sum \text{base operating DRG payments for PN}
\] (2)

\[
Aggregate\ payments\ for\ all\ discharges = \sum \text{base operating DRG payments for all discharges}
\] (3)

\[
Ratio = \left[ 1 - \frac{\text{Aggregate payments for excess readmissions}}{\text{Aggregate payments for all discharges}} \right]
\] (4)

\[
Readmission\ Adjustment\ Factor = \begin{cases} 
FY\ 2013: \text{the higher of the Ratio or 0.99 (1% reduction)} \\
FY\ 2014: \text{the higher of the Ratio or 0.98 (2% reduction)}
\end{cases}
\] (5)

Formulas to Compute the Readmission Payment Adjustment Amount

\[
Wage\ adjusted\ DRG\ operating\ amount = \text{DRG weight} \times \left[ (\text{labor share} \times \text{wage index}) + (\text{nonlabor share} \times \text{cola}) \right]
\] (6)

\[
Base\ Operating\ DRG\ Payment\ Amount = \text{Wage adjusted DRG operating amount} + \text{new technology payment}
\] (7)

\[
Readmissions\ Payment\ Adjustment\ Amount = [\text{Base operating DRG payment amount} \times \text{readmissions adjustment factor}] - \text{base operating DRG payment amount}
\] (8)
Equation 1 is calculated by the CMS through hierarchical-logistic modeling which incorporates aspects of hospital demographics, such as patient severity on admission, as well as variations in overall numbers of patients. An interesting aspect is that if other hospitals improve their performance, this changes the prediction for our hospital system. This is applied individually on each DRG in equation 2. The ratio in equation 4 is then compared to the overall reduction per year which the CMS has defined. The higher of the two is selected. The final calculation of the Readmission Payment Adjustment Amount is calculated from the base operating payment adjustment amount listed in equation 7, and the readmission adjustment factor already presented in equation 5. However the readmission adjustment factor is always less than 1, which yields a payment adjustment amount which will be negative. This will always be a payment reduction to the hospital system. As the above changes show, if a hospital system cannot reduce their readmission rate to a level which can avoid penalties, they will face a financial burden. However, whatever the strategy to reduce the readmission rate, it must remain cost-effective. Otherwise penalties will still be applied, along with the cost of any readmission reduction strategies. We see that this can pose a difficult problem to solve.

Exacerbating the problem, is a secondary issue which is prompted by the necessity of managing costs associated with readmission reduction programs. As the readmissions account for only a small percentage of the patients, the vast majority of patients require no interventions. As such, an initiative which targets all patients being discharged would be particularly wasteful. However that still leaves the issue of being able to identify those patient which would be likely of readmission. This is a difficult aspect of the problem as there are a multitude of reasons or characteristics which may be responsible for hospital readmissions among the patients, and quite likely differing ones for each of the separate diagnoses.

So we have a situation in which determining the optimum solution represents a non-trivial problem. We are faced with determining the following;

- What interventions to use
- How large should our intervention recipient group be
- Which specific individuals should be targeted
- What is the financial outcome

All of which are subject to several constraints in determining the solution for the optimum readmission reduction strategy. Consider the following constraints;

- Effectiveness of interventions (and changes based on reductions)
- Cost of interventions
- Additional staff required
- Staff duty reallocation
- Reimbursement reduction
- Improvements made by cohort hospitals
- Budget constraints

All of this must happen in an environment in which the use of experimentation to determine the strategy is largely imprudent. The outcomes of experimental trials would be on actual patients. Beyond this ethical aspect, is the more practical problems associated with running experiments in which the variation between individual subjects is high, and the length of time required to generate sample sizes which are large enough would be proscribed. Moreover the managerial concerns of constructing an intervention program, even on a trial basis would be large. Also consider that a choice like this might very well require additional staff to accomplish. It would be problematic to go through a hiring process to implement a trial program, as the times to fill positions, especially skilled ones can be quite long. Put simply, the readmission reduction strategy cannot be of the guess and check variety, but must be well thought out, analytics driven strategy, as the timeliness of implementation is significant, and financial impact of these decisions is high.

What we propose in the solution of the problem represents a method whereby hospitals may leverage the existing literature from case studies on readmission reduction initiatives, information which cannot be achieved internally,
and combine that with internally derived analytics. From the information on effectiveness, we tie in the estimated financial costs associated with the specific hospital, and the readmission reduction which might be expected if a given strategy is employed. We utilize machine learning on the hospital patient information to formulate a risk prediction model which surpasses the accuracy of the statistically based models found in literature. At this point, the elements of the problem are assembled, and the remaining task is to define the optimization problem for the solution of which patients should be targeted to receive each intervention. Thus a hospital can generate an optimum strategy for the reduction of readmissions, all the while minimizing the financial losses due to reductions in reimbursements.

2. Literature Review

The current literature which focuses on readmissions is largely based in two separate directions. One centers around the intervention strategies. There are countless methods which have been trialed and analyzed. For CHF, these methods fall into multiple strategies. Some methods tried include multi-disciplinary teams,[5], patient education based interventions[6], home monitoring[7], support[8] and transitional care[9]. These differing types of trials have been attempted in varying ways. However what these papers describe is the intervention which was tried, the population which it was trialed on, and the outcomes achieved. In rare cases, the scope is expended to incorporate the financial aspects such as the cost of interventions, however this is not always the case. For an intervention strategy to be effective, there must be an accounting of cost. In order to implement a readmission reduction strategy, we must first determine if the effort will be cost-effective.

In the other category is the articles which examine the prediction of the readmission risk of patients. One study examined the efficacy of utilizing a bedside test for B-type peptide levels, as B-type peptide is secreted from the ventricles or lower chambers of the heart in response to pressure changes, of patients.[10] Similarly, C-reactive protein was also examined.[11] Data mining techniques have also been aimed at the problem, in some cases aimed at creating prediction models. [12,13] Many examine which factors may be predictive of heart failure readmission, but do not propose models for risk assessment.[14-16]

However what these papers lack is what hospital systems truly need. To be able to bridge the gap between having a description of the interventions strategies, and a method of prediction. For only when we are able to connect the two, is the problem bounded. If we are able to know how much an intervention costs, how effective it is, and who can receive it, then we are able to determine an optimum strategy which gives the proper intervention mix to the population.

3. Methods

The current work is focused on conveying that there exists a method for determining the applicability of optimization methods, rather than attempting to define the optimal parameters of the genetic algorithm.

3.1 Genetic Algorithm

The genetic algorithm is an optimization heuristic which requires two parts to be implemented. They draw from evolutionary computing, a subset of artificial intelligence. The first is a genetic representation of an individual solution to the problem. The other is a method for evaluating that solutions effectiveness. The algorithm begins with the generation of several possible solutions. These represent the starting generation. From this point, the solutions will be evolved from this group iteratively. Each parent generation will create a child generation through reproduction, which is composed of

![Figure 2: View of the Genetic Algorithm](image-url)
two mechanisms. The initial is often referred to as crossover. A representation of this can be seen in the following figure. Beyond this combination of the features or genes of the parents is a subsequent mutation. By this mean, the solution can be created from the genes of the previous generation, however will still possess the ability to shift in new directions in the solutions space which have into been explored previously.

![Parent Generation](image)

![Two-point Cross-over](image)

![Child Generation](image)

Figure 2: Representation of the two point crossover mechanism which is used in this research

The method for representing possible solutions genetically is very much similar to the formation of a vector of numbers. For this work in which we compare four intervention strategies, and using a sample of three-hundred patients. The solution space can be represented by a vector which is 8 units long. To define a solution, we are essentially looking at which patients are receiving which interventions. In order for this to work effectively, it is necessary to arrange the patients themselves into a vector which is increasing or decreasing in risk probability. Thus treatments will be assigned contiguously, thus targeting a population subset which will be between two risk scores. A representation of this idea can be seen in the figure below.

![High Risk](image) ![Low Risk](image)

Figure 3: Patient risk is laid out sequentially, with patients at highest risk listed first

In order to define the solutions space, we need to have the definition for each of the intervention strategies. To define this, we are able to use two measurements, the start point, and the length of the vector. This is done for each intervention strategy resulting in 8 units for the vector, as seen below.

Individual: The Genetic representation is shown below

![Gene Representation](image)

Description of each gene in individual

<table>
<thead>
<tr>
<th>Gene</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>Starting point of intervention 1</td>
</tr>
<tr>
<td>b</td>
<td>Length of intervention 1</td>
</tr>
<tr>
<td>c</td>
<td>Starting point of intervention 2</td>
</tr>
<tr>
<td>d</td>
<td>Length of intervention 2</td>
</tr>
<tr>
<td>e</td>
<td>Starting point of intervention 3</td>
</tr>
<tr>
<td>f</td>
<td>Length of intervention 3</td>
</tr>
<tr>
<td>g</td>
<td>Starting point of intervention 4</td>
</tr>
<tr>
<td>h</td>
<td>Length of intervention 4</td>
</tr>
</tbody>
</table>

Figure 4: Representation of the solution vector format used
The components of this genetic algorithm rely on the calculation of a patient's risk of readmission. We have discussed these briefly in the literature review. In the formulation of this experiment we utilize the best methods of prediction of risk for our patient population which has been done to date. A random forest model has been created using hospital records which predicts which patients will be readmitted. One method of displaying the results of such machine learning is a Receiver-Operator Characteristic (ROC) curve which gives the trade-off between true-positive and false-positive rates. The risk of each patient is predicted with the random forest, and the risk profile acts as an input risk vector for the genetic algorithm.

Example: 10 patient problem
Solution: (1, 5, 0, 0, 0, 0, 0, 0)

Patients Receive Intervention 1

Start Point = 1
Length = 5

Figure 5: Showing the translation from the solution vector format to that used in the application of interventions to patients.

Figure 6: ROC curve for the prediction of readmission in CHF patients from a random forest model.
3.2 Constraining Equations

The problem which we are focused on defining outputs the results based on \( p \) patients, which will be receiving some or none of the \( i \) interventions. Each patient will have a risk of readmission \( \beta_p \). The risk reduction associated with the \( i^{th} \) intervention is \( \gamma_i \). The cost of a given intervention is \( c_i \) and the resulting risk post intervention would be \( \epsilon_p \).

When we consider the reduction in readmission risk, it would seem that the results of multiple interventions should not be additive. For example, a patient \( p \) who has risk \( \beta_p \) should after having intervention 1 and 2 applied would not expect

\[
\epsilon_p = \beta_p - (\beta_p \cdot \gamma_1) - (\beta_p \cdot \gamma_2)
\]  

(9)

as it is not plausible that applying multiple interventions to a single patient will achieve the full reduction from both as there is often some overlap between interventions. Contrarily it is not plausible that there would be no additional benefits to multiple interventions. As such, we utilized a method whereby there is an exponential reduction in the patients risk reduction benefits. For this study, we use a degradation factor \( \delta_i \) such that

\[
\delta_1 = 1; \quad \delta_{n+1} = \delta_n / 2
\]

(10)

Therefore we may define

\[
\epsilon_p = \beta_p - (\beta_p \cdot \delta_1 \cdot \gamma_1) - (\beta_p \cdot \delta_1 / 2 \cdot \gamma_2)
\]  

with \( \delta_1 = 1 \)

(11)

therefore

\[
\epsilon_p = \beta_p - (\beta_p \cdot \gamma_1) - (\beta_p \cdot 1 / 2 \cdot \gamma_2)
\]

(12)

with

\[
\gamma_1 > \gamma_2 > \gamma_3 > \cdots > \gamma_i
\]

(13)

which gives the reduction in the efficacy is applied to those interventions which are less effective than others. For instance if one intervention has a reduction of 50\%, and another 25\%, a patient sill receive the full reduction from the 50\%, but will only receive a 12.5\% reduction from the second.

A valid solution is one such that in solution vector \( V \) of length \( n \)

\[
\begin{cases}
V_n < p; \text{ for odd } n \\
(V_{n-1} + V_n < p; \text{ for even } n \\
V_n \geq 0 \text{ for all } n
\end{cases}
\]

(14)

Our goal is the overall goal is the calculation of overall cost, being that the optimization of overall financial return \( \phi \) is the goal. In this way, we define that the overall financial impact is the aggregate case charges, assessment of the cost of interventions, cost of readmissions, but saving on readmissions prevented. In order to calculate this quantity, it is necessary to represent the case charges for each patient \( \psi_p \). Which is able to be transferred into the readmission adjusted payment amount \( \chi_p \) by the transforms in equation 1 through 8. Note this adjustment causes a zero return for readmissions \( \chi_p' \). The distribution of case charges is found as follows.
\[ \psi(x) = \frac{\left(\frac{x - \mu}{\beta}\right)^{\gamma - 1} e^{-\left(\frac{x - \mu}{\beta}\right)}}{\beta \Gamma(\gamma)} \quad x \geq \mu; \gamma, \beta > 0 \]  

(14)

where \( \gamma \) is the shape parameter, \( \mu \) is the location parameter, \( \beta \) is the scale parameter, and \( \Gamma \) is the gamma function which has the formula

\[ \Gamma(a) = \int_0^\infty t^{a-1}e^{-t} \, dt \]  

(14)

\[ \varphi = \sum_{i=1}^{p} x_{p} - \sum_{i=1}^{p} x'_{p} - \sum_{i=1}^{p} \sum_{i=1}^{c} c_{ip} \]  

(15)

3.3 Results

The results of the optimization experiment outline above was conducted by utilizing a 20 parent set, or a population size of 20. As well, we selected a crossover rate of 90%, mutation rate of 1%, with basic roulette wheel selection. We selected 4 separate intervention approaches in the set of possible intervention approaches. In the set of interventions we used a risk reduction of 10, 20, 30, and 40 percent, and a cost of intervention at 20, 400, 2000, 16000 respectively. As has been stated previously, the population used to test the algorithm was set at 300 patients which have been randomly selected from the pool of patients.

The calculation of patients risk was determined by utilizing a random forest classification model which we had created. This is the measurement which is used at the end of the results to determine what cut-points or cut-off criteria should be used in the assignment of new patients toward intervention groups. Each patient which was
selected from the pool of patients has a calculated risk score, as well as a known cost of case, and outcome with respect to readmission. The final outcomes of patients may be altered by the application of interventions. Essentially, we are looking at the patients which were readmitted to the hospital, and based on the patients risk reduction $\epsilon_p$, re-rolling their result. If the patient is prevented from being readmitted this change shows in the reduction for $\chi_p'$. The final results of the algorithm found a solution at $(12,245,45,200,19,3,76,4)$ after 2000 iterations without improvement.

4 Discussion

The results of the algorithm show that the solution point which drifts towards favoring the less costly, but less effective interventions. However these results are not transferable as the current results are based on a facsimile of the true values which would be required to define the optimum solution for a hospital system to utilize for their readmission reduction efforts. We also see that on the expensive interventions, the length of application vector is quite small, indicating that a near zero would be a reasonable option, indicating that there is little benefit in using this type of readmission intervention. However all that would be required to define the optimal point is the insertion of the true costs of the hospital system with regard to interventions, as well as to determine the applicable risk reduction parameters which would be assigned to the intervention strategies that an organization would consider. As well, the risk reduction hinges upon the risk prediction which is assigned to the patients. If that risk score associated with the patients are incorrect, then the overall applicability of the optimization modeling will be much reduced in impact.

The work presented above shows that it is possible to use hospital specific information to perform an optimization of this type. An extension of the work is in progress, utilizing the optimization approach for the selection of an intervention reduction strategy in a local community hospital system. For this work, we will be utilizing a literature review for the selection of several possible intervention efforts. We will be including the staffing costs from the hospital system, as well as inclusion of the capacity limitations which may be imposed on certain intervention strategies. For the inclusion of these capacity limitations, we may simply append these to the equation 14 for valid solutions such that a solution which violates these intervention capacity limitations will not be accepted. Beyond this, we are able to utilize the information from cohort performance to alter the impact on equations 1-8, although this will need to be handled hypothetically, as we are not able to know which interventions or to what extent competition will utilize, and as such will not be aware of the readmission rates which will be seen in those organizations. For instance, if cohort systems are able to align a large amount of resources toward readmission reduction efforts, or conversely determine that no investment will be made, would push in differing directions. This influence may possibly shift the decisions which would be made in optimization.

Also we face uncertainty from literature. While we assume that the intervention strategy will have the same reductions as reported, this may vary. A method to address this would be through sensitivity analysis. This could be done by altering the reported performance of selected interventions a certain percentage. This could either be randomly applied, or use a grid approach. Future work should include an assessment of how robust the solution remains.

Another aspect which may prove to be interesting is to consider the intervention strategy not only on the annual basis but looking long-term. If large investments are being made on readmission reduction, the predicted readmissions for the next year would be lessened. This may pose a difficulty for a hospital system as it would make it difficult to improve in future.

5 Conclusion

With many hospital systems struggling to face the coming changes to their reimbursement with regard to performance in preventing readmissions, there is a large opportunity available to develop solutions for the problem. The approach that we propose is a way to leverage the existing literature in both the prediction of patient readmission, and the literature on intervention effectiveness from case studies. Without a method which can guide the creation of a comprehensive approach to readmission reduction, the system faces the risk that another system in
the cohort will outperform in this regard, thus protecting their own reimbursements, but leveling large penalties against their own. The approach we propose would allow a hospital to find the optimum solution, yielding the largest financial gain, and may be tailored to the specific system with the use of the data from the institution with regard to staff wages, intervention costs, and case charges.

References


