A method for determining an emergency readmission time window for better patient management.

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Abstract

This paper introduces an modelling approach to determining the appropriate width of a time window within which an admission is classified as a readmission. The approach is based on an intuitive idea that patients, who are discharged from hospital, can be broadly considered as consisting of two groups – a group that is at high risk of readmission and a group that is at low risk. Using national data from the London area (UK), we demonstrate its usefulness in the case of chronic obstructive pulmonary diseases (COPD), one of the leading causes of early readmission. Although marked regional differences exist for the optimal width of the time window for COPD patients, our findings are largely inline with figures used by the government, hance provide some support for the use of 28 days as the time window for defining COPD readmissions. The novelty of this modelling approach lies in its ability to estimate an appropriate time window based on evidence objectively derived from operational data. Therefore, it can provide a means of monitoring performance for hospitals, and can potentially contribute to the better management of patient care.

1. Introduction

Generally, high level of emergency and unplanned readmission is potentially associated with poor patient care. Therefore readmission rate is a key element in the performance rating framework for National Health Service (NHS) hospitals in the UK [5]. In this paper, we will only study readmission in the context of emergency and unplanned readmission since planned readmission is simply a part of the care plan for a patient. Currently the NHS performance rating framework defines readmission as an emergency or unplanned admission to the same hospital within 28 days following discharge [5]. However, there is a lack of consensus in the literature on the appropriate choice of time interval in defining readmission [1]. Literatures concerning readmission are mostly focused on studying the clinical and social factors that are influential to readmission [6]. However, these studies are often inconclusive and contradict each other. Sibbritt [11] validated the use of 28 days in the definition of readmission by constructing histograms of time between successive hospital admissions for four specialities: medical, surgical, paediatrics, obstetrics and gynaecology. For each specialty, the distribution of time between successive admissions exhibited a log-normal or exponential shape with approximately 32% of admissions occurring within 28 days after discharge. A similar pattern was found by Chambers *et al* [2], where time between successive admissions was showed to have an early peak (0-6 days), and then gradually levelled off after 28 days. However in both cases, the justification for the choice of 28 days relied solely on visual inspection of the histograms, therefore, it could result in an inaccurate estimation. As a result, performance ratings of NHS trusts may be misleading.

In this paper we propose a modelling approach to systematically tackle the issue surrounding the appropriate choice of a time window within which an admission is classified as a readmission. The paper is organised into the following sections: the modelling approach in presented in Section 2; in Section 3, we demonstrate the usefulness of such an approach in the case of chronic obstructive pulmonary diseases (COPD), one of the leading causes of early readmission [6]; discussion and comments on future works are in Section 4.

2. Modelling Approach

2.1. General Framework

We may think of the population of patients discharged from hospital to the community as divided generally in

Proceedings of the 19th IEEE Symposium on Computer-Based Medical Systems (CBMS'06)
0-7695-2517-1/06 $20.00 © 2006 IEEE

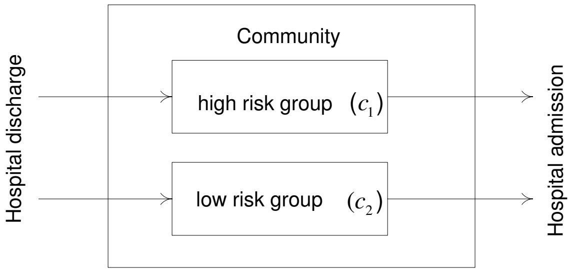

Figure 1. Illustration of two groups of patients in community following hospital discharge.

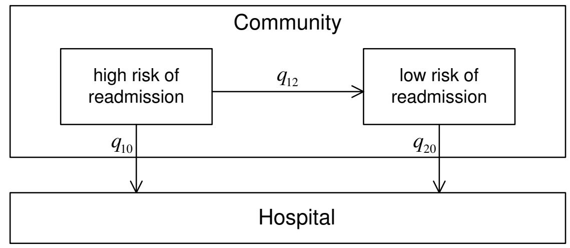

Figure 2. Coxian phase-type model for the phases patients experience in the community before admission to hospital.

two groups, namely, one of patients at "high risk" of readmission (denoted as c_1), and the other of patients at "low risk" of readmission (c_2). These two groups will have different readmission pattern. This is illustrated in Figure 1. However, for each patient, we observe the time between successive hospital admissions (called *time to admission*), and do not know which group the patient belongs to. Therefore, the random variable time to admission (denoted by X) can be expressed as to follow a mixture distribution with probability density function (pdf)

$$f(x) = pf_1(x) + (1-p)f_2(x), \tag{1}$$

where p is the probability of a patient being in group c_1, and $f_1(x)$ and $f_2(x)$ are the pdf of time to admission for group c_1 and c_2 respectively.

Given the observed time to admission for a patient, the probability of belonging to c_1 (and respectively c_2) can be determined from the posterior probability expressed via the Bayes' theorem as $p(c_1|x) = pf_1(x)/f(x)$ (and respectively $p(c_2|x) = (1-p)f_2(x)/f(x)$). Using the Bayesian classification argument [4], one can show that the optimal way to assign the group membership of a patient with observed time to admission x is: assign to c_1 if $p(c_1|x) > p(c_2|x)$; and c_2 otherwise. In other words, the optimal cut-off in time to admission that "best" separates the high risk group and the low risk group is determined by solving $p(c_1|x) = p(c_2|x)$ for x, or equivalently given by the time value where $pf_1(x) = (1-p)f_2(x)$, that is, where the two corresponding curves intersect. Therefore, we propose that the period from following a hospital discharge to the identified cut-off point is the optimal time window that determines whether an admission is a readmission.

2.2. Coxian Phase-type Model

In their effort to graphically determine a time window for emergency readmission, Sibbritt [11] and Chambers *et al* [2] recognised implicitly the existence of a change in the risk of readmission. That is the risk for readmission is high soon after a hospital discharge and the risk is substantially reduced after a period of time in the community. This can be represented as a two-phase model as illustrated in Figure 2). Following discharge, patients go first through a phase of high risk of readmission, when they are more likely to be readmitted, possibly because of premature discharge from their previous hospital stay; if not readmitted during this phase, they enter another phase of low risk of readmission and stay longer in the community. In Figure 2, the rate q_{12} represents the transfer rate from phase 1 to phase 2; and q_{10} and q_{20} are the admission rates from phase 1 and phase 2 respectively, where subscript 0 represents the state being in hospital.

If we assume that all rates (i.e. q_{12}, q_{10} and q_{20}) are constant, then the time to admission follows a Coxian phase-type distribution [3], which describes the distribution of time to absorbtion of an absorbing continuous-time Markov chain where the transient states are structured in a sequential manner. This approach, which takes a process point of view, can be shown [8] to be equivalent to the patient group argument presented in Section 2.1. In particular, the pdf of the mixture distribution (1) can be expressed by in terms of rates as

$$p = \frac{q_{10} - q_{20}}{q_{10} + q_{12} - q_{20}} \tag{2}$$

and $f_1(x)$ and $f_2(x)$ are exponential density functions with parameters $\lambda_1 = q_{10} + q_{12}$ and $\lambda_2 = q_{20}$ respectively. Therefore, the optimal cut-off time x^* is computed by

$$x^* = \frac{1}{\lambda_1 - \lambda_2} \ln \left[\frac{p\lambda_1}{(1-p)\lambda_2} \right]. \tag{3}$$

Given a set of data on time to admission, the rates are estimated by fitting Coxian phase-type distributions to the data via the method of maximum likelihood. General numerical optimisers such as those available in MATLAB and R can be used to maximise the likelihood function.

Table 1. Levels of readmission (as defined using 28 days) for COPD in the London area for calendar years 1998 to 2003.

	1998	1999	2000	2001	2002	2003
Number of admissions	96,841	101,819	98,470	99,795	101,970	112,918
Readmissions using 28 days time window	8,239 (28.0%)	9,492 (24.2%)	10,272 (23.1%)	11,062 (22.3%)	11,598 (22.2%)	12,756 (22.0%)

Table 2. Levels of readmission for COPD at different width of the time window among the five strategic health authorities (SHA) in the London area.

	NWL	NCL	NEL	SEL	SWL
Number of admissions	18,999	11,566	18,889	18,728	11,971
Readmissions using 14 days time window	1,251 (17.6%)	810 (16.1%)	1,488 (16.9%)	1,254 (15.3%)	721 (14.2%)
Readmissions using 21 days time window	1,690 (23.8%)	1,106 (21.9%)	1,977 (22.5%)	1,698 (20.8%)	952 (18.7%)
Readmissions using 28 days time window	2,032 (28.7%)	1,362 (27.0%)	2,438 (27.8%)	2,133 (26.1%)	1,185 (23.3%)
Readmissions using 35 days time window	2,353 (33.2%)	1,575 (31.2%)	2,822 (32.1%)	2,472 (30.2%)	1,421 (28.0%)
Readmissions using 42 days time window	2,665 (37.6%)	1,759 (34.9%)	3,142 (35.8%)	2,767 (33.9%)	1,557 (30.6%)

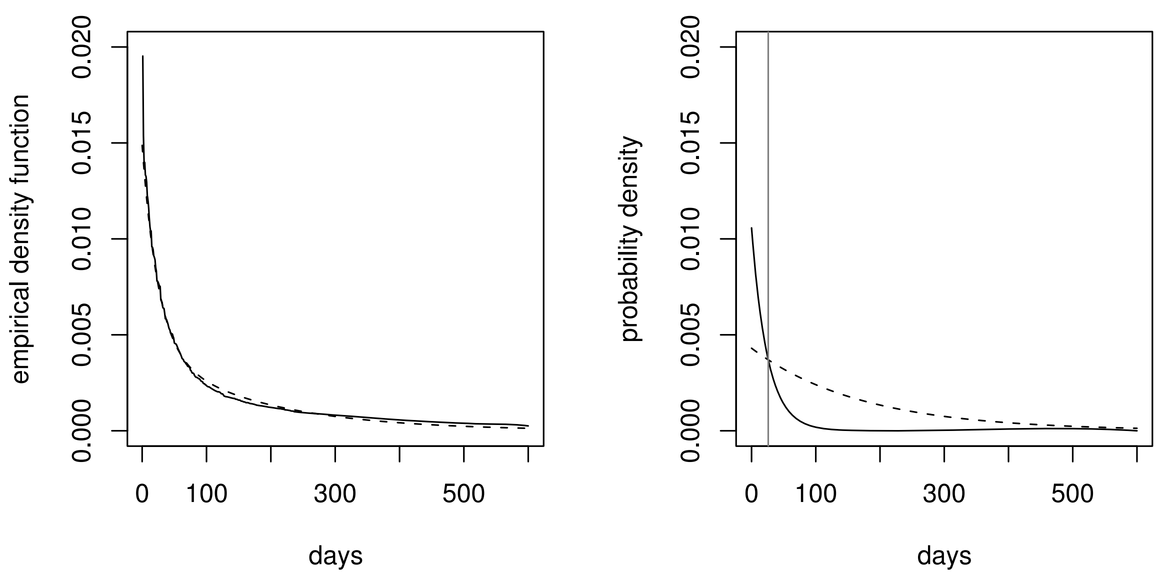

Figure 3. Empirical (solid line) and fitted (dotted line) density function of time to admission for the COPD data (left); and illustration of the identification of the optimal time window for the case of COPD (right). The curves represent the two terms in (4) (the first term in solid line and the second term dotted line). The vertical line indicates the point of intersection.

3. Application

3.1. Data

The Department of Health in the UK releases annually the national database – Hospital Episode Statistics (HES). The HES dataset captures all the consultant episodes of a patient during their stay in a hospital in the UK. During a hospital stay (or called spell), a patient might encounter several successive episodes. We focus our study on chronic obstructive pulmonary diseases (COPD), which is one of the leading causes of early readmission [6], in the London area. Spells end with discharge by death are excluded as no further admission is possible. Furthermore, since death in community is not recorded by the HES data, we have no information on the up-to-date status of a patient who was discharged alive. As a result, we limited our data selection to patients who had a subsequent admission following a discharge. Since our aim is to study patients who are admitted to hospital soon after their discharge, this data selection procedure is justified.

Using the HES dataset from 1997 to 2004, we extracted 962,656 episodes from patients who had the primary diagnosis code corresponding to COPD (ICD-10 codes J40-J44). A set of 696,911 completed spells were derived from the episode data for calendar year 1998 to 2003. Since HES is released based on financial years (in the UK, a financial year is from 1 April to 31 March the following year), necessary steps were taken to restore the data to be based on calendar years. For each patient, the time between successive spells is the observed time to admission.

Using the time window of 28 days as currently defined by the Department of Health, we observed that, although the number of admissions was mostly increasing during 1998 to 2003, the percentage of readmission actually showed a decreasing trend from 1998 to 2000 and remained relatively stable from 2001 to 2003 (see Table 1). This decrease could be due to the UK government's keen effort in using readmission rate as one of the key measurements to rank the performance of NHS hospitals.

The NHS in London is managed by five strategic health authorities (SHA) that map onto five regions: North East London (NEL), North Central London (NCL), North West London (NWL), South East London (SEL) and South West London (SWL). We therefore partition the data according to region and investigate regional variation in readmission rates. In addition, we vary the width of the time window to be 14, 21, 28, 35 and 42 days to study its effects on readmission rate. Table 2 shows, for each SHA, the number of admissions, the number and percentage of readmissions at each width of the time window. Regional variation in readmission rates is noticeable. SWL, which has the lowest level of COPD admission, consistently has the lowest percentage of readmission for all the time windows considered. On the other hand, NWL consistently has the highest percentage of readmission despite having comparable number of COPD admissions with NEL and SEL during the period. We can only speculate the causes of such marked regional variation in readmission rate for COPD. One possible cause could be due to deprivation differences among the regions. A recent study in the Greater Manchester area (UK) [7] showed that deprivation indeed exerted a significant effect on the risk of emergency readmission.

3.2. Results

We applied the modelling approach outlined in Section 2.2 to the COPD dataset. Using the whole dataset, we estimated the rates of the model depicted in Figure 2 as $q_{12} = 0.02548$, $q_{10} = 0.01487$ and $q_{20} = 0.00583$. Thus the pdf of time to admission for COPD patients are estimated to be

$$f(x) = 0.010572e^{-0.04035x} + 0.004303e^{-0.00583x}. \quad (4)$$

All the fitting was done using the open source program R [9].

Figure 3 (left) shows the empirical and the fitted pdf (4) of time to admission for the COPD dataset. The close agreement between these two curves suggests that the model with two phases, high risk and low risk of readmission phases, is able to capture the overall pattern of time to admission for COPD.

Given the estimated rates, for COPD, the optimal width of the time window, within which a subsequent admission is classified as a readmission, is computed using (3) to be about 26 days. This is graphically illustrated in Figure 3 (right) where the two curves represent the two terms in (4) and the vertical line indicating the point of intersection at about 26 days. This time window is very similar to the one defined by the Department of Health. The probability of belonging to the high risk (of readmission) group is estimated (using (2) to be at about 26% for a COPD patient who is just discharged from hospital. This figure is largely inline with the percentage of readmission given in Table 1, which 28 days was used as the time window.

We also fitted the model to data from each of the five SHAs in the London area. Table 3 summarises the estimated optimal time window for each SHA together with their corresponding probability of being in the high risk group. Clearly there is a marked difference in the estimated optimal time window among the regions. SWL, which has the lowest level of readmission as shown in Table 2, has the smallest time window and the lowest probability of being in the high risk group following a discharge. Our estimate suggests that the optimal time window for SWL in the case of COPD is a third less than the government

Table 3. Optimal time window for the five London SHA and probability of being in high or low risk readmission.

SHA	Optimal time window (days)	Probability of belonging to the high risk group
NEL	31.8	0.302
NCL	28.2	0.278
NWL	28.8	0.288
SEL	26.9	0.271
SWL	18.7	0.212

published figure. On the other hand, NEL has the largest estimated time window and almost a third of its discharged COPD patient is at high risk of being readmitted. With the exception of SWL, the estimated optimal time windows for all the SHAs are still largely inline with the 28 days that is used by the Department of Health. Therefore, our findings provide some support for the use of 28 days as the time window in defining readmission in the case of COPD.

4. Discussion and Future Work

In this paper, we have introduced an modelling approach to determining the appropriate width of a time window within which an admission is classified as a readmission. This approach is based on the intuitive idea that patients, who are discharged from hospital, can be broadly considered as consisting of two groups – a group that is at high risk of readmission and a group that is at low risk.

Using national dataset, we showed that, in the case of COPD patients, there are potential problems in how to measure readmission rate. In particular, marked difference in what constitute a readmission for a diagnosis group exists among different regions. Given that the NHS performance rating framework regards readmission rate as one of its key measurements, some hospitals may in principle be disadvantaged by the use of one single number to define a time window. Our findings suggest that more research is needed to understand emergency readmission.

The model we presented in Section 2.2 assumes there are only two phases that patients will experience during their stay in the community. We recognise that this can be restrictive in practice. Therefore, during the application of this model to the COPD data, we tested models with one, two and three phases. Models with two phases were consistently shown to provide the "best" fit, judging by the Bayesian Information Criterion (BIC) [10], which is a measure of goodness-of-fit taking into account the complexity of the model. Future work will be directed at extending this modelling approach to a more general situation.

The novelty of this approach lies in its ability to estimate an appropriate time window based on evidence objectively derived from operational data. Furthermore, this method can easily be implemented as a software toolkit to estimate optimal time windows for different diagnosis groups across regions, hence providing a means of monitoring performance for hospitals. Therefore, this can be a valuable tool in helping to tailor hospital care to local needs and ultimately contributes to better patient management.

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