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Modeling the impact of care transition programs on patient outcomes and 30 day hospital readmissions

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ABSTRACT

The increasing adoption of care transition programs – interventions designed to reduce hospital readmissions – has introduced a new challenge of evaluating such programs, i.e., assessing their impact on patient outcomes and care quality. This is difficult given the limited availability of program outcome data and analytical feedback exchange between providers. Moreover, the temporal nature of the effects of scheduled interventions on patient health raises the question of selecting and applying methodological tools appropriate for scientific research in this area. Our aim is to provide such methodological guidance and assist analysts, healthcare providers, and policy makers with extracting meaningful insights regarding the impact of care transition programs based on available data. We explore two well-known modeling approaches, Cox models and Markov chains, and using an illustrative example, demonstrate how they can be translated into informative analytic models with sufficient flexibility to analyze programs with diverse structures. We show that Cox Proportional Hazard models are particularly useful for identifying variables with the greatest impact on readmissions and quantifying the benefits of patient participation in a readmission reducing program. Extended Cox models provide an understanding of the effects of influential variables on readmissions as they change throughout the recovery period, allowing assessment of the relative benefits of care transition programs on different patient populations at specific times following a hospital discharge. Discrete Time Markov Chain models are particularly useful for assessing the impact of care transition programs in terms of expected time to readmission, facilitating the comparison of alternative program designs on patient outcomes.

1. Introduction

In recent years, the healthcare industry has been facing increasing pressure from providers, payers, and consumers to reduce care delivery costs while improving the quality of care. This substantial challenge has resulted in rapid changes in the design and delivery of healthcare services, especially initiatives designed to reduce costly hospital readmissions. The Hospital Readmissions Reduction Program, enacted as part of the Patient Protection and Affordable Care Act (PPACA), further catalyzed this movement as it introduced financial penalties for hospitals with excess readmission rates associated with a specific subset of diagnoses [1].

Care transition programs, or a series of actions designed to improve care coordination and continuity during critical patient transitions between providers and locations of care [2], have become a popular approach to reducing costly readmissions and improving patient outcomes following a hospitalization [3–7]. With the increased prevalence and variety of programs designed to improve the safety and effectiveness of transitions from hospital to home, policy makers and healthcare administrators are faced with the new challenge of evaluating the impact of these programs on patient and organizational outcomes.

It is clear that assessing the impact of healthcare interventions on patient and organizational outcomes is essential to achieving high quality and cost effective care, yet this problem has not yet been definitively studied nor have practical analytic solutions been developed. Finding answers to relevant questions, including: “How effective is our program at reducing hospital readmissions?”, “Which patients benefit most from our program?”, and “Do patients benefit more from Program A or Program B?”, are critical to the continued development and optimal application of these interventions. However, answering these questions can be a daunting task for organizations with limited data and analytic resources.

For this work we adopt the perspective of a community based care organization, such as a primary care practice or home health care agency, which administers a care transition program and seeks to understand the impact of the program on patient health outcomes.

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Further, we focus on patient risk of readmission in the first 30 days following a hospital discharge as the key characteristic of health outcomes, to align with the aims of the Hospital Readmissions Reduction program. This paper sets out to help an analyst possessing sufficient readmission program data in conducting quantitative studies of the program's impact. Specifically, we elaborate on how some accepted modeling and inference methods can be used to extract practical and meaningful insights from program outcome records.

In this effort, we look at two viable modeling approaches, Cox regression and Markov chains, both of which have found use for modeling various complex healthcare processes with time-dependent elements. We first present the theoretical foundations of these approaches, and then, using an illustrative example, provide guidance for developing the corresponding analytic models for the outlined readmission analysis problem and how to use the resulting models to produce administrative policy related insights.

2. Background

2.1. Statistical modeling of healthcare processes

Understanding the impact of care transition programs on patient health outcomes requires a detailed and quantifiable knowledge of the key factors influencing these outcomes. Statistical models are effective methods for defining the relationship between multiple variables and time to readmission.

Using survival analysis, a particular form of statistical model, one can model the time until the occurrence of a particular event, e.g. death, or for this research, hospital readmission. Within the domain of survival analysis, Cox modeling methods can describe time to readmission as a function of one or more covariates, or explanatory variables; a model would output patient's hazard as a particular measure of risk.

Standard, or time-stationary, Cox models work under the proportional hazard assumption, which states that hazard, or the risk of an event occurring, is constant over time. This assumption greatly simplifies model specification and analysis while providing robust results. Since the Cox proportional hazard model was first introduced [8], this approach has been widely used to model a variety of healthcare processes, including hospital readmissions and mortality [9–12] making it an ideal initial approach for this research.

For many healthcare processes, however, it is impractical to consider time-stationary variables or to meet the requirements of the proportional hazards assumption. When considering a time to readmission event it is conceivable that the passage of time may have a variable effect on model covariates and outcomes, violating this fundamental assumption. The extended Cox model relaxes the proportional hazard assumption allowing time-varying covariates to affect the analysis. This approach has been used to model dynamic healthcare processes, such as identifying factors that influence fetal and infant death in the time immediately before and after birth [13], and identifying prognostic factors of disease progression when these factors change over time [14]. We consider the extended Cox model in this work as an important alternative to the standard Cox model: this extension provides a dynamic understanding of a patient's risk of readmission, as influenced by the dynamic covariates, during the period immediately following a hospital discharge.

The two statistical models we developed evaluate the impact of care transition programs on patient health outcomes and overcome the challenges of adequately representing the complexities of these programs. We demonstrate how the widely applied time-stationary Cox model can identify the key variables that influence patient readmission risk following an initial hospitalization and guide organizations in the development of appropriate measures and evaluation strategies. The extended Cox model provides a more dynamic view of patient readmission risk following a hospitalization that can be used to compare the impact of care transition programs on different patient populations further informing the design and implementation of these programs.

2.2. Stochastic modeling of healthcare processes

Analysts seeking a more advanced understanding of the impact of care transition programs, beyond quantifying the influence of individual factors on time to readmission, should consider stochastic modeling approaches. Stochastic processes are capable of capturing the inherent complexities of care transition programs as they evolve during the patient recovery process. Ideally suited for modeling dynamic programs, stochastic models capture time-varying changes while simultaneously considering the interaction of multiple factors. Using stochastic modeling approaches we can understand the expected outcomes of care recovery processes and intervention programs, including anticipated resource use, associated costs, and patient health outcomes, while adequately representing the dynamic and inherently random nature of the process.

A particularly attractive use of stochastic models is to support clinical decision-making. A subset of stochastic models, known as state transition models (STMs), provide a flexible and intuitive way to compare patient outcomes under alternative treatment scenarios. STMs represent stochastic processes as a series of mutually exclusive and collectively exhaustive states. These models are further defined by a set of allowable transitions between the states and a set of transition probabilities that represent the likelihood of each of these transitions occurring. Time is represented in the cycle length and is typically a discrete and uniform period of time chosen for its clinical relevance or to match evaluation times. A key assumption of STMs, is the Markovian property, which states that transition probabilities are independent of previous process states and the time spent in these previous states.

Markov models, a particular form of STM, have been widely used in the healthcare domain for economic evaluations and medical decision making [15–17]. For example, Markov models have been used to model disease progression [15,17] and to understand patient movements throughout a segment of the care continuum. Several studies have viewed the patient recovery process as a continuous time Markov model [18–20] for purposes of long term analysis and resource planning. Other studies have accounted for the time dependence of transition decisions by using Semi-Markov models to depict the recovery process [21–23]. In these models, movement between states is affected by both the current state and the time spent in that state. Semi-Markov models have also been used to analyze the steady state behavior of a system including the number of patients per state, the probability of a patient being in a particular state at a particular time, and long term resource planning. A final set of research reduced the complicated recovery process into several phases, each of which is comprised of several independent, yet unobservable, states [18,24]. Because of the highly individualized nature of health care, specifically the patient recovery process, healthcare processes are well suited for continuous time and Semi-Markov models. Few models employ a discrete time Markov model, however the use of bed census data as an input has allowed the analysis of resource requirements and costs related to in-hospital patient movements [25,26].

The Markov model we developed provides an alternative analysis approach that can be used to compare the impact of complex healthcare interventions on patient health outcomes, particularly when these programs have different underlying structures. Integrated into clinical decision support systems the Markov model would provide important new insights to guide healthcare organizations in matching their at-risk patient populations to the most effective available program.

From a practical perspective we believe that the adaptation of widely used and understood statistical and stochastic modeling approaches to this complex problem significantly reduces the barriers associated with such modeling activities, particularly for organizations that are challenged with limited access to patient level data, program