

Preface

The quest for quality in healthcare has led to attempts to develop models to determine which providers have the highest quality in healthcare, with the best outcomes for patients. However, it is not possible to compare providers directly without knowing something about the patients treated. A patient with diabetes, kidney failure, and congestive heart failure is very sick. If such a patient were to also get a serious infection, that patient will have a higher risk of death compared to a patient with a broken leg. Therefore, we must find a way to compare the severity of patients. We need to be able to identify which patients are sicker compared to others; this is difficult to do. Is a patient with congestive heart failure more or less sick compared to patients with liver or lung cancer? Once we can define a patient severity index, we need to use it to rank the quality of care across providers. We also need to be able to define what a high quality of care actually means.

We can examine patients for each separate procedure or reason for hospitalization. For example, we can look at all patients who are admitted for cardiovascular bypass surgery. However, many of these patients also have co-morbidities such as cancer and diabetes. Is it more or less risky to perform bypass surgery on a patient with diabetes, or on a patient with cancer? How does a patient rank with high cholesterol and blood pressure, but no other specific co-morbid problems? What if that patient also has asthma?

In addition, since there are so many different patient problems, it becomes extremely difficult to consider them all. If we only consider some of them, how do we choose which ones to consider and which ones to omit? Suppose we omit some patient conditions that turn out to have a high risk of mortality? Moreover, if we only use some conditions, and some providers (but not others) know which conditions are used to rank quality, do those providers have an advantage compared to those who do not know the model? They can focus on just the conditions in the model instead of having to look at all patient conditions. It becomes easier to show that a provider has more severe patients if that provider knows what conditions to record to define severity.

The purpose of this book is to discuss the general practice of defining a patient severity index. Such an index serves several purposes, amongst them to make risk adjustments to compare patient outcomes across multiple providers with the intent of ranking the providers in terms of quality. Another use is to determine which patients will need more care because of the severity of illness. As a specific example, a severity index can determine which patients are most at risk for infection while in the hospital to determine which patients might benefit from prophylactic treatment. It extends the work of an earlier text, *Risk Adjustment*, edited by Lisa Iezzoni in 2003 (Chicago, Hospital Administration Press). This book focuses on how severity indices are generally defined. We also examine the consequences of the models, and we investigate the general assumptions required to perform standard severity adjustment. Because the assumptions are rarely satisfied, other methods should be used that can investigate the model assumptions, and that can be used when standard assumptions are not valid. We will also look at how the severity index is used to rank the quality of providers. We examine whether these rankings are valid and reliable.

Chapter 1 gives a general introduction to the patient severity indices, and also a general introduction to the healthcare datasets that will be used throughout the book. We also give a brief introduction to SAS Enterprise Miner®, which is used throughout the book to examine the data. We do assume that the reader is familiar with basic SAS coding. If not, we suggest that you study *The Little SAS Book: A Primer*, 3rd Edition by Lora D. Delwiche and Susan J. Slaughter or *The Little SAS Book for Enterprise Guide 4.1* by the same authors. Both books are available through SAS Press, Inc. The SAS software is the most versatile for investigating the complex data needed to define patient severity indices.

Because of the size of the datasets used to define patient severity, traditional statistical methods are not equipped to analyze the data. Therefore, we will introduce data mining techniques that have been developed in marketing and networking to investigate large databases. Data mining is a general term that is used to represent several steps when working with data. The primary outcome is not to test hypotheses; it is to make decisions that can be used in healthcare to improve care while simultaneously reducing the cost of care. In this book, we will demonstrate why data mining techniques are superior to traditional statistics when using the large datasets typically used to define patient severity indices.

Chapter 2 demonstrates the use of data visualization, especially kernel density estimation. Data visualizations, including the standard graphs, are invaluable when extracting knowledge about the data. We are concerned with the entire population distribution and not just with comparing averages. Because we are usually dealing with heterogeneous populations, we cannot assume that the population is normally distributed. Therefore, we need a technique that can provide an estimate of that distribution, and can model outcomes from such populations.

Chapter 3 discusses several statistical methods that are the primary techniques currently used to investigate health outcomes, including linear and logistic regression. In addition, it examines model assumptions for regression, especially the Central Limit Theorem. In contrast, Chapter 4 discusses the data mining technique of predictive modeling. It demonstrates how predictive modeling encompasses the more standard techniques of linear and logistic regression, but expands options to improve the potential of decision making from the data. Predictive modeling uses many different diagnostic tools to determine the effectiveness of the model.

Chapters 5, 6, and 7 discuss the patient severity indices defined by the Charlson Index, the All Patient Refined DRG, and resource utilization. All three of these indices suffer from a lack of uniformity when information is entered by different providers. For this reason, some providers can take advantage of the methodology to improve their quality rankings without actually improving the quality of care. The Charlson Index is publicly available and can be calculated given patient diagnosis codes. The other two coding methods are proprietary and not as readily available. However, we can examine the results of these severity measures.

Chapter 8 shows a novel method of text mining to define an improved patient severity index; one that can be validated using patient outcomes since it is defined independently from the outcomes. Moreover, it is not susceptible to the “gaming” that results from the variability in the terms of the coding mechanisms. Providers cannot take advantage of this variability to improve their standing. We can discover who is shifting patients into a higher severity category.

Chapter 9 demonstrates how to use patient claims data to define a severity index. It is more complicated to use since different providers use different coding methods. Hospitals generally use ICD9 codes; physicians use CPT or HCPCS codes. These coding methods are not equivalent. In particular, HCPCS codes can document more detail compared to ICD9 codes.

Chapter 10 examines the recent development of using reimbursements to reward providers who rank high using quality measures that in turn depend upon patient severity indices. We examine the data to determine whether those providers who game the system can be identified through an analysis of billing data. We also investigate the ability of these indices to determine whether infections are nosocomial (meaning hospital acquired), or community acquired. Providers are changing policy and will no longer reimburse providers for nosocomial infection.

Both Chapters 8 and 10 discuss in detail the issue of nosocomial infection. Currently, most risk adjustment methods focus upon patient mortality only without considering complications, errors, and infections. However, infection is also a major concern; patients want to know that a hospital stay will not make them sick. There is a problem of under-reporting nosocomial infection, so there needs to be a way to identify which infection is nosocomial versus community acquired. We also want to be able to anticipate problems, especially since providers will now be required to pay for the treatment of such infections. The ability to prevent infections by giving those at high prophylactic treatment is important, and can be examined using the same billing information now used to define patient severity indices.

Throughout this book, we will rely on public data readily available. In particular, the Medical Expenditure Panel Survey collects data on all household and individual usage of healthcare, including physician visits, inpatient and outpatient care, and medications. Costs, and the payer(s) of these costs are also available in the data. The National Inpatient Sample requires a small fee, but is also readily available for analysis purposes. Both datasets are representative of the data collected by clinics and hospitals during the routine of treating patients.

Another type of data that is readily available, although proprietary, is claims data. It is more complicated than the data in the nationally collected databases. In particular, different types of providers use different coding methods to list patient diagnosis information. Hospitals use ICD9 codes; physicians tend to use CPT or HCPCS codes. Inpatients receive bills from the hospital, and from each physician who provides any type of treatment while the patient is in the hospital, even if that treatment is just to examine the patient record. The different claims, providers, and codes need to be combined in some way to define an episode of care so that different episodes can be sequenced, and the different outcomes of care can be considered.

In fact, the number one issue in any definition of a patient severity index is to determine the best way to handle all of the codes that are used to represent patient conditions, and patient treatments. There are thousands of possible codes. There is no good way to include all of them in a statistical model. For this reason, some method of compression must be used; the most common compression method is to limit the number of codes used in the model, either to the codes that are the most frequent, or the ones that are the most crucial. The Charson Index, discussed in Chapter 5, is a good representative of this type of compression.

A second method is to examine each and every diagnosis code and related co-morbidities, and to assign a level of severity to each combination of conditions. This can be very difficult to do. The APRDRG index defined in Chapter 6 utilizes this method. Panels of physicians are used to arrive at a consensus as to the level of a patient's condition based upon co-morbidities to the primary diagnosis. Another method is to use patient outcomes to assign a level of severity as opposed to using the patient diagnoses, under the assumption that a more severe patient will use more treatment resources and have a higher risk of mortality. This approach is used in the disease staging measures discussed in Chapter 7.

It is important that patient severity indices convey accurate information. Unfortunately, there is no "gold standard" that allows us to compare models of patient severity to a standardized outcome. There-

fore, any severity index must be considered carefully, and the statistical methodology used to develop the index must be adequate. The results should be validated in some way in the absence of a gold standard. All of these issues will be developed in this text. However, we will discuss in more detail the issue of validating the model in Chapter 11.

In addition, we will examine the ranking of quality providers while adjusting for the severity of a patient's condition. Moreover, we will demonstrate additional uses for the process of defining severity indices. It is important to investigate thoroughly just how well patient severity indices accurately identify a patient's true severity and how accurate the resulting ranking of provider quality actually is. It is particularly important to ensure that the indices are truly meaningful and that the amount of gaming is limited so that those who provide high quality care are identified as providing high quality.