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Two models to investigate Medicare fraud within unsupervised databases

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ABSTRACT

We propose two models to identify fraud, waste and abuse in Medicare. These models are used to flag health care providers. The motivation for these models is based on observed cases of fraud. The paper details the use of clustering algorithms, regression analysis, and various descriptive statistics that are components of these models. Some of the challenges in the struggle to reduce fraud in Medicare are discussed.

1. Introduction

It is clear that fraud plays an important role in the US healthcare system. It increases the cost of healthcare through direct and indirect means. Its direct impact includes fraudulent monetary charges to the healthcare system. It also has indirect impacts which mainly arise from false positive identifications of fraudulent health care providers. These include opportunity costs associated with the medical education of the fraudulent providers and costs associated with the construction of complicated policies that effect beneficiaries and providers alike.

The general goal of organizations charged with fighting fraud can be formulated as reducing direct and indirect costs by maximizing the percentage of correct identification of fraudulent providers while minimizing the false ones with the least amount of resources. This paper exposes the application of two methodologies to identify fraudulent infusion therapy drug providers in a number of states from an unsupervised database.

The models employed in fraud identification can be generalized into two categories. There are models that identify fraud after observing nearly irrefutable amount of evidence, for instance identifying providers that charge for services rendered amounting to more than 24 h a day. On the other hand there are models which can identify providers of interest as being possibly involved in fraud after observing abnormal patterns in the data. The false positive rates for these models are likely to be higher. The models exposed in this paper belong to the latter category where we argue for their necessity in decreasing the overall level of fraud in the healthcare system.

The paper is organized in six sections. Section 2 is an overview of healthcare fraud investigations within US and provides a review of recent work in the literature but is not meant to be a comprehensive literature review. Section 3 provides an overview of data and Section 4 provides the exposition of the two models that we use to investigate fraud. In Section 5 we demonstrate the application of the methods. Section 6 includes the results and conclusion.

2. Overview

Anderson and Hussey (2001) present a bleak picture of the US healthcare system's performance when they compare the health care systems of 29 OECD countries. The comparison is made through various healthcare indicators among these countries. The authors find that for many of these indicators between the years 1960, 1980 and 1998 US' relative performance either did not improve or decline. The authors point out that US spends more than twice the median expenditure per capita among the OECD countries. They point out the larger GDP per capita of US relative to other OECD countries as a major component of this difference. However the authors also note that even when the GDP per capita is taken into account, there is still a large difference between observed and expected US healthcare expenditures. The authors' conclusion does not change when expected health care expenditures are calculated from the benchmark value of Switzerland, second ranked country in terms of health care expenditures per capita.

Anderson, Frogner, and Reinhardt (2007) investigate the health expenditures in the OECD countries. The authors are consistent in their findings with Anderson and Hussey (2001) and report that US spends more than 2.5 times per capita than the median country included in the study. Furthermore the authors report that US had fewer physicians, nurses, hospital beds, doctor visits and hospital days, per capita than the median OECD country. The authors' conclude that there are two major reasons why per capita spending is so much higher in USA. They suggest higher GDP per capita and higher prices account for these measures.

Part of the problem of higher prices lays in costs to the government programs arising from Fraud, Waste and Abuse (FWA). Li,

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Huang, Jin, and Shi (2008) cite two different impact estimates. National Healthcare Anti Fraud association gave a conservative 3% estimate (60 Billion) of annual healthcare expenditure. FBI also reports the higher level of fraud at 10% (170 Billion).

By definition fraud requires intention on the part of the provider. Unfortunately we do not have any method to identify intention from the data. Therefore the methods outlined in this paper will also include in its goal to flag providers involved in waste and abuse. We use the term fraud below, instead of fraud waste and abuse for convenience.

Efforts to reduce fraud are complicated by several factors. There were more than 40 million beneficiaries that were eligible for Medicare part A and part B programs (Hoffman, Klees, & Curtis, 2008). Each year, these beneficiaries utilize services which result in terabytes of data. In other words, manual inspection of medical records is practically impossible. Heuristics that detect fraud such as duplicate claims within a database are useful but insufficient to catch but the most simplistic fraud. Furthermore, beneficiaries and health care providers are not homogenous. What constitutes as *normal* utilization rates and payments per claim of an oncologist is different from the *normal* utilization rates and payments of a family practitioner. The healthcare needs of a beneficiary will be dependent on his/her diagnosis and the provider's assessment of his/her individual needs. There are a large quantity of possible diagnosis and assessments. These factors lead to a large non fraud related variance in utilization and money amount paid per beneficiary. This adds to the challenge of, detecting abnormal patterns in data, which is the prevalent approach in detecting fraud within unsupervised databases.

Additional complications arise due to the dynamic nature of the system associated with healthcare fraud. Among the main components of this system are those who are charged with controlling and those who are agents of, fraud. In 1996, The Health Insurance Portability and Accountability Act (HIPAA) created the Health Care Fraud and Abuse Control Program (HCFAC). This program, as stated by the Department of Health and Human Services And The Department of Justice Health Care Fraud and Abuse Control Program Annual Report (2007) is "... designed to coordinate federal, state and local law enforcement activities with respect to health care fraud and abuse." The prevailing approach in the program emphasizes the monetary amount "recovered" as a result of investigation and targets those providers for whom an "extreme level" of evidence have been gathered. For instance the 2007 annual health care fraud and abuse control program report has two sections in its executive summary section. These are listed as monetary results and enforcement actions. In the monetary results section, the dollar amount earned for the federal government as well as the amounts transferred to the Medicare and Medicaid programs is listed. The monetary amounts listed involve the fiscal year 2007 as well as the total amount earned since 1997, the beginning of the HCFAC program. The enforcement actions list the number of cases that have been opened in 2007 as well as the number of defendants involved in these cases. The choice of the words in the titles for these sections as well as the lack of historical perspective in the enforcement actions section is implicative of the mindset in controlling fraud. The budget for the federal government in 2004 includes a section on performances of various programs (Performance and Management Assessments Budget of the United States Government Fiscal Year, 2004). The report states for the HCFAC program, "While providing some information on the status of fraud and abuse activities, the existing goals – return on investment, expected recoveries, and program savings – do not objectively measure if the program achieves its mission. The current measures do not demonstrate whether health care fraud and abuse have decreased, which is the program's ultimate mission." The Whitehouse archives contain a document on HCFAC "Detailed Information on the Health Care Fraud and Abuse Control Assessment" (2002) that refers to ongoing improvement plans which include quantitative measures of performance. However these measures do not address the issue raised by the 2004 report mentioned above.

As implied by Bolton and Hand (2002), Li et al. (2008) the prevalent methodology in the detection of fraud within unsupervised databases involves detecting possible outliers from claim amounts or utilization rates. We can classify providers involved in fraud in two broad categories of those who are high profile and those who are not. We use the term high profile providers as those providers who claim services to such an extent as to draw themselves attention in simple outlier models. The majority of the models employed in unsupervised databases target high profile providers which are relatively easier to identify. These models, in general have high true positive rates. For instance the *impossible days* model identify providers who charged for services that lasted longer than 24 h in a single day. The news release by the United State Attorney's Office District of Rhode Island (2008) indicates the successful application of this model. As useful as these models that target high profile providers are, if they are the only ones that are employed, they will not lower overall extent of fraud in Medicare. If these models are the only ones that are employed in fighting fraud, it would be unlikely to identify providers involved in fraud who take a more cautious approach. Even though the type of models this paper exposes would naturally have a higher false positive rate they can identify providers from the class of providers who are not high profile.

We use the term *behavioral* to describe the models in this paper as they are constructed to identify fraud based observed fraud cases. There are two major reasons why fraud investigation within unsupervised databases does not usually involve the type of models we expose in the paper. First of all, even though there is no formal comparison, it is likely that behavioral models flag more false positives than outliers of utilization rates and this increases costs to the healthcare system. Second of all, monetary amounts recovered by the agencies as a result of judgments or settlements are an explicit evidence of the work being done rather than the effect on the level of existing fraud in Medicare. It is unfortunate that cost of false negatives and the dynamic nature of fraud is not a major concern in the literature.

We outline two methods to detect possible fraud. We use clustering methodology to group zip code areas in terms of socioeconomic factors. We identify providers with outlying rates of utilization within these relatively homogenous regions. The second method includes a definition of an impractical distance traveled for health care services and we flag providers based on the measures involving the claims above this distance.

It is clear that many providers who are flagged in these studies are innocent of fraudulent activity and a secondary analysis that requires the participation of beneficiaries and providers is necessary to minimize overall costs to the system.

3. Data

The database consists of claims belonging to beneficiaries requiring the utilization of infusion therapy drugs. This database has several characteristics that have implications for any type of fraud investigation. First, there are three types of physician identifiers. Not all identifiers are uniquely associated with a provider. Furthermore providers can use a combination of these identifiers within their claims. In other words the identifiers are not consistently populated for all claims of an individual provider. Some group providers also have identifiers listed in these fields. For some of these fields, individual providers are not distinguishable. In addition carriers can have their own rules to assign one of these