A Fraud Resilient Medical Insurance Claim System

Yuliang Shi[1], Chenfei Sun[1], Qingzhong Li[1], Lizhen Cui[1], Han Yu[2], Chunyan Miao[2]

[1]School of Computer Science and Technology, Shandong University, Jinan, China

[2]Joint NTU-UBC Research Centre of Excellence in Active Living for the Elderly, Nanyang Technological University, Singapore

shiyuliang@sdu.edu.cn, sun.chenfei@163.com, {lqz, clz}@sdu.edu.cn, {han.yu, ascymiao}@ntu.edu.sg

Abstract

As many countries in the world start to experience population aging, there are an increasing number of people relying on medical insurance to access healthcare resources. Medical insurance frauds are causing billions of dollars in losses for public healthcare funds. The detection of medical insurance frauds is an important and difficult challenge for the artificial intelligence (AI) research community. This paper outlines *HFDA*, a hybrid AI approach to effectively and efficiently identify fraudulent medical insurance claims which has been tested in an online medical insurance claim system in China.

Introduction

Medical insurance frauds are causing billions of dollars in losses for public healthcare funds around the world. According to estimates by the Federal Bureau of Investigation (F-BI), healthcare frauds cost American tax payers over US$80 billion a year (Aldrich, Crowder, and Benson 2014). Detecting medical insurance frauds is an important and difficult challenge. As more medical insurance claims are being filed and processed online, claimants' behavior trajectory big data can be tracked during the claim process. However, because of the complex granularity of data, existing fraud detection approaches face difficulties in recalling fraudulent claim behaviors (Musal 2010; Liu et al. 2015).

Traditional fraud detection techniques use rules designed by experts as a basis to identify fraudulent behaviors based on assessing if any of these rules have been violated (Ngai et al. 2011). As medical insurance claim activities move online, data-driven approaches for medical insurance fraud detection has now become a distinct possibility. The combination of behavior trajectory big data and machine learning techniques offer promising solutions to the medical insurance fraud problem. Human behaviors have two main attributes: 1) *category* and 2) *frequency*. Existing intelligent medical insurance fraud detection methods focus on detecting either abnormal categories of behaviors or abnormal frequencies of behaviors (Phua et al. 2010). The accuracy of these methods are often affected by the complex granularity of behaviors.

To address this problem, we outline the hybrid fraud detection approach (HFDA) system which has been incorporated into the Dareway Medical Insurance Claim System in China. Through the proposed Semi-Supervised Isomap (SSIsomap) behavior clustering method, the Simple Local Outlier Factor (SimLOF) outlier detection method and the Dempster's Rule of Combination (Shafer 1976) based evidence aggregation method under HFDA, the system can detect abnormal categories and frequencies of behaviors simultaneously to help guard against medical insurance frauds.

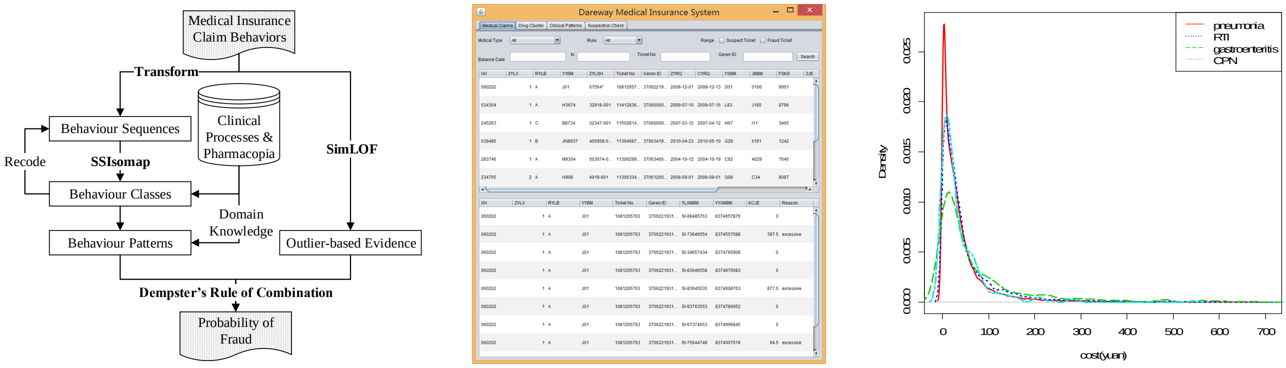
The HFDA System

The HFDA system can be divided into four modules as illustrated in Figure 1(a):

1. Transforming the data records into behavior sequences;
2. Obtaining behavior pattern-based evidences through the proposed SSIsomap method;
3. Obtaining outlier-based fraud evidences through the proposed SimLOF method; and
4. Combining the two sources of evidences to determine the probability of fraud through Dempster's Rule of Combination.

In an online medical insurance claim system, there can be millions of transactions from a large number of user-s. In order to make better sense of the users' actions, it is advantageous to organize the transactions into behavior sequences. Firstly, the history claims can be transformed into behavior sequences. This can be achieved by collecting relevant information from the claimants and other stakeholders through the system interface. The Dareway Medical Insurance Claim System, which is being used by Zibo City in China, collects information about the claimant, the hospital and the approving authorities as shown in Figure 1(b). Then, the clustering results for the behavior trajectory data are saved and expert users can modify these results to incorporate their domain knowledge. The behavior patterns are shown to the approvers and transformed into rules which are used to determine the presence of fraud in future claims.

As medical insurance claim data for each claimant tend to be sparse, peer group comparison is favored over self-comparison when it comes to outlier-based fraud detection. Therefore, we need to first obtain the behavior distribution-s of many claimants. The HDFA system analyzes the daily cost distributions of different groups of claimants (Figure 1(c)) to build up a baseline to identify outliers. For new



(a) The HFDA system.

(b) The medical insurance claim submission user interface of the Dareway Medical Insurance Claim System.

(c) Daily cost distributions of different groups of claimants.

Figure 1: The system architecture, interface, and results from HFDA.

claims, the proposed SimLOF method looks for groups of related applicants and check if the new expenditure is within the baseline distribution.

With the obtained pattern-based evidence and the outlier-based evidence, the HFDA system calculates the probability of fraud for new claims using Dempster's Rule of Combination (Shafer 1976). Claim approvers can check the status of new claims through the HDFA system. Records highlighted in red indicate high probabilities of fraud.

Discussions and Future Work

HFDA serves as a useful tool for medical insurance claim approvers to leverage people's behavior trajectory data to combat frauds. In future research, we will design decision support mechanisms to recommend suitable actions against potential medical insurance frauds for claim approvers. Human factors concepts such as emotion (Yu et al. 2010), curiosity (Yu et al. 2011), reputation (Yu et al. 2013), wellbeing considerations (Yu et al. 2014a) and decision-making characteristics (Yu et al. 2014b) will be explored to help the HFDA interface agent build trust with the users. The behaviour trajectory data in wellness games (Cai et al. 2014) will also be incorporated into HFDA for analysis.

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