Analysis and Application of Data Mining in CRM Systems of Healthcare Insurance

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Abstract
Data mining techniques in Customer Relationship Management (CRM) has a very important role in the practice; it is an important means of gaining and maintaining customer information, and improving customer value. We have determined to compare a variety of techniques, approaches and different tools and its effect on the healthcare field. Data mining created new concept with customer relationship management where different companies can gain a reasonable advantage. The goal of data mining is to turn data into facts, figures, or text which can be processed by a computer into knowledge or information. The main reason of data mining application in healthcare systems is to create a mechanical tool for make out and distributes relevant healthcare information. The aim of this paper is to make a detailed study report of diverse types of data mining applications in the healthcare sector and to minimize the difficulty of healthcare data transactions. A relative study of different data mining applications, techniques and different methods applied for takeout knowledge from database produced in the healthcare industry.

Keywords
Data Mining, healthcare system, healthcare industry, Customer Relationship Management (CRM).

I. Introduction

There are many businesses developing day by day. Inside it, the financial side of customer relationships is changing in elemental ways. Now days, Companies are facing the need to put into operation new resolution and policies that are helpful to these changes. Companies have to increase customer value through analysis of the customer choices. The tools and technologies of data warehousing, data mining, and other customer relationship management (CRM) techniques give new openings for businesses.

Businesses like insurance do not just deal with customers in order to make transactions; they turn the opportunity to sell products or services into a service experience and endeavor to establish a long-term relationship with each customer.

In healthcare, data mining is becoming increasingly popular and essential. Many techniques are used for existence of medical insurance scam and misuse, for example, many healthcare insurers effort to reduce their losses by using data mining tools to help them find and path unlawful.[3] Fraud detection using data mining applications is common in the commercial world, for example, in the detection of bogus credit card transactions. Recently, there have been reports of successful data mining applications in healthcare fraud and abuse detection.[2] The most common and important applications in data mining most likely involve predictive modeling. Classification refers to the forecast of a target variable that is definite in nature, such as predicting healthcare fraud vs. no fraud. Estimation, on the other hand, refers to the prediction of a target variable that is metric (i.e., interval or ratio) in nature, such as forecast the length of processing or the amount of reserve operation. There are many commonly techniques used which include old statistics, such as multiple distinguish analysis and logistic regression analysis. Many non-traditional methods are also developed in the areas of artificial intelligence and machine learning. Many important models are also used like neural networks and decision trees.

II. Data mining: an overview

A. Definition:

"Data mining" is a refined data search capability that uses statistical algorithms to discover patterns and correlations in data [4]. Data mining can be defined as the process of finding previously unknown patterns and trends in databases and using that information to build predictive models [1]. Data mining is an old technique—it has been used by many institutions like financial institutions, for credit scoring and fraud detection; marketers, for direct marketing ; retailers, for market segmentation and store layout; and manufacturers, for quality control other processes.

B. The evolution of data mining:

Data mining techniques are the result of a long research and product development process. In the development stages from data to useful information, each stage is dependent on previous ones.
Table I shows the evolutionary stages from the viewpoint of the user.

Table I Evolutionary Stages of Data Mining

Stage	Business question	Enabling technologies	Product providers	Characteristics
Data Collection (1960s)	"What was my average total revenue over the last five years?"	Computers, tapes, disks	IBM, CDC	Retrospective, static data delivery
Data Access (1980s)	"What were unit sales in New England last March?"	Relational databases (RDBMS), Structured Query Language (SQL), ODBC	Oracle, Sybase, Informix, IBM, Microsoft	Retrospective, dynamic data delivery at record level
Data Navigation (1990s)	"What were unit sales in New England last March? Drill down to Boston"	On-line analytic processing (OLAP), multidimensional databases, data warehouses	Pilot, IRI, Arbor, Redbrick, Evolutionary Technologies	Retrospective, dynamic data delivery at multiple levels
Data Mining (2000)	"What's likely to happen in Boston unit sales next month? Why?"	Advanced algorithms, multiprocessor computers, massive databases	Lockheed, IBM, SGI, numerous start-ups (nascent industry)	Prospective, proactive information delivery

C. *Applications of data mining:*

Data mining tools take data and create a reflection of reality in the form of a model. It shows patterns and associations in the data. According to process orientation, data mining activities fall into three general categories (see Fig. 1):

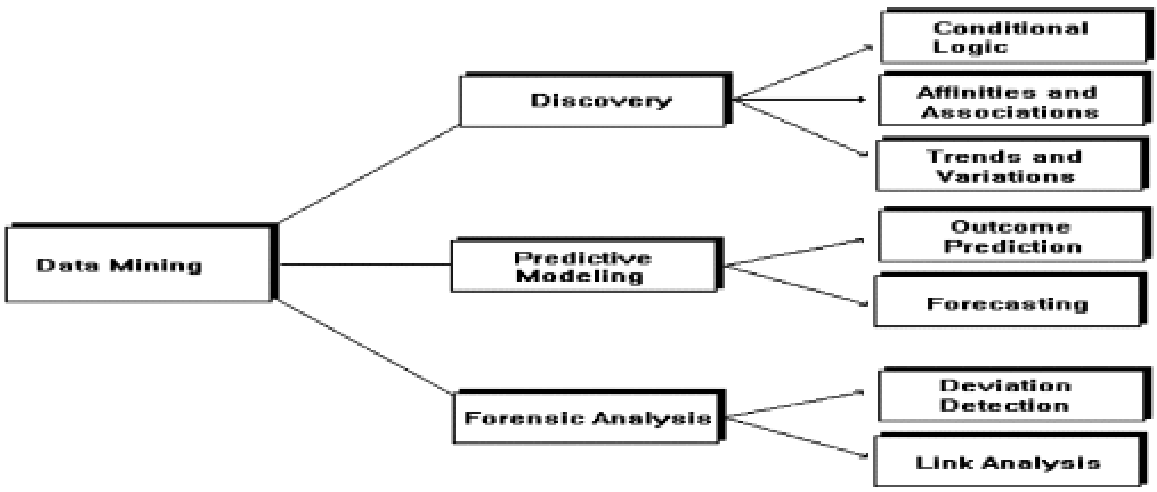

Fig 1: Breakdown of data mining from a process orientation. Source: Information Discovery, Inc. [8]

Data mining is used to construct six types of models aimed at solving business problems: classification, regression, time series, clustering, association analysis, and sequence discovery [10].

The first two, classification and regression, are used to make predictions, while association and sequence discovery are used to describe behavior. Clustering can be used for either forecasting or description.

D. Different types of data mining techniques:

A top-level breakdown of data mining technologies is based on data preservation. In other words, is the data retained or discarded after it has been mined? (see Fig. 2). In early approaches to data mining, the data set was maintained for future pattern matching. The retention-based techniques only apply to tasks of predictive modelling and forensic analysis, and not knowledge discovery since they do not distil any patterns, as shown earlier in Fig. 1.

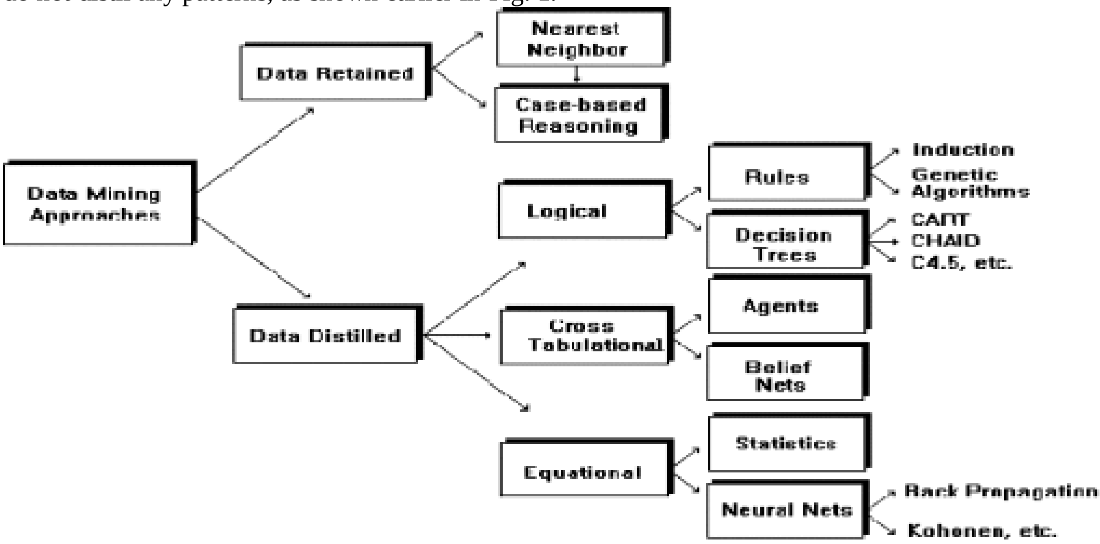

Fig 2: Different types of Data Mining Techniques

III. Customer relationship management- An outline

A. Definition:

There are four elements of a simple CRM framework: Know, Target, Sell, Service [5]. CRM involves firm to know and understand its markets and customers.

Customer Relationship Management (CRM) is a business viewpoint involving identifying, understanding and better providing for your customers while building a relationship with each customer to improve customer satisfaction and maxi profits. It's about understanding, predicting and countering to customers' needs.

Business has to manage customer relations and their customer needs. Businesses have to collect correct information, organize them to analyse and proper action. Business has to keep that information up-to-date, must be accessible to employees, and provide information employees to convert that data into products better matched to customers' needs.

CRM is about not to collect data but how to interpret data is also important. In this term Data Mining techniques are useful.

IV. Data mining and CRM

CRM is very broad concept one of which is data mining, and that data mining is a method or tool that can aid companies in their quest to become more customer-oriented. Now we need to step back and see how all the pieces fit together.

A. The association / relation:

"customer lifecycle" refers to the stages in the relationship between a customer and a business. It is important to understand customer lifecycle because it relates directly to customer revenue and customer profitability. There are three ways to increase a customer's value:
(1) increase their use (or purchases) of products they already have; (2) sell them more or higher-margin products; and (3) keep the customers for a longer period of time [6].

In general, there are four key stages in the customer lifecycle:

1) Prospects—people who are not yet customers but are in the target market

2) Responders—prospects who show an interest in a product or service

3) Active Customers—people who are currently using the product or service

4. Former Customers—not appropriate customer

The customer lifecycle provides a good framework for applying data mining to CRM. On the "input" side of data mining, the customer lifecycle tells what information is available. On the "output" side, the customer lifecycle tells what is likely to be interesting [6].

V. Data mining applications in health care insurance

Data Mining can be used in various ways, like efficiency, management of healthcare; Customer Relationship Management; and detection of fraud and abuse. Predictive methods can be used.

Fraud and abuse: Data mining applications are used to detect fraud and abuse often establish norms and then recognize unusual or abnormal patterns of claims by physicians, laboratories, clinics, or others. These applications can highlight inappropriate prescriptions or transfer and fake insurance and medical claims.

VI. Limits of data mining

Data mining applications can really benefit the healthcare industry. It may be limited by the accessibility of data, because the raw inputs for data mining often exist in different settings and systems, such as administration, clinics, laboratories and more. Many times, researchers discussed that Data mining might be costly because before application of data mining, data warehouse has to prepare, which is costly.

Positively, a clinical data repository, sharp care case-mix system, laboratory information system, ambulatory case-mix system, and health plans database—and used to find and implement better evidence-based clinical solutions.

A sufficiently exhaustive mining of data will certainly yield patterns of some kind that are a product of random fluctuations.[9] This is especially true for large data sets with many variables. Hence, many interesting or significant patterns and relationships found in data mining may not be useful.

Fourthly, the successful application of data mining requires knowledge of the domain area as well as in data mining methodology and tools. Without a sufficient knowledge of data mining, the user may not be aware of or be able to avoid the pitfalls of data mining. [15] Collectively, the data mining team should possess domain knowledge, statistical and research expertise, and IT and data mining knowledge and skills. Finally, healthcare organizations developing data mining applications also must make a substantial investment of resources, particularly time, effort, and money. Data mining projects can fail for a variety of reasons, such as lack of management support, unrealistic user expectations, poor project management, inadequate data mining expertise, and more. Data mining requires intensive planning and technological preparation work. In addition, physicians and executives have to be convinced of the usefulness of data mining and be willing to change work processes. Further, all parties involved in the data mining effort have to collaborate and cooperate.[7]

VII. Future guidelines

Data mining applications in healthcare insurance can have marvellous probability and worth. However, the techniques of Data mining are helpful to pivot on the availability of clean healthcare data. Health Care Industry considers how data can be better captured, stored, prepared, and mined. Possible directions include the standardization of clinical vocabulary and the sharing of data across organizations to enhance the benefits of healthcare data mining applications. Further, as healthcare data are not limited to just quantitative data, it is necessary to also explore the use of text mining to expand the scope and nature of what healthcare insurance data mining can currently do. In particular, it is useful to be able to integrate data and text mining.[16] It is also useful to look into how digital diagnostic images can be brought into healthcare data mining applications. Some progress has been made in these areas.[37],[38]

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