Chapter 2
The Use of Artificial Intelligence Systems for Support of Medical Decision-Making

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ABSTRACT

There is a treasure trove of hidden information in the textual and narrative data of medical records that can be deciphered by text-mining techniques. The information provided by these methods can provide a basis for medical artificial intelligence and help support or improve clinical decision making by medical doctors. In this paper we extend previous work in an effort to extract meaningful information from free text medical records. We discuss a methodology for the analysis of medical records using some statistical analysis and the Kohonen Self-Organizing Map (SOM). The medical data derive from about 700 pediatric patients' radiology department records where CT (Computed Tomography) scanning was used as part of a diagnostic exploration. The patients underwent CT scanning (single and multiple) throughout a one-year period in 2004 at the Nagasaki University Medical Hospital. Our approach led to a model based on SOM clusters and statistical analysis which may suggest a strategy for limiting CT scan requests. This is important because radiation at levels ordinarily used for CT scanning may pose significant health risks especially to children.

INTRODUCTION

Text-mining is applied in various fields to extract useful and previously unknown information contained in databases and texts. In the field of bioinformatics significant efforts are being made in genome sequencing, protein identification, medical imaging, and patient medical records. This study continues the efforts to mine patient medical records that consist of clinician notes in the form of free

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text. Harris et al (2003) developed a system to extract terms from clinical texts. Using natural language processing techniques, i.e., a parser, the MedLEE system, Jain et al (1996) turned free-text from patient records into an output with structured information. For example, this system may identify patients with tuberculosis based on chest radiographs. To do this it uses a corpus of controlled vocabulary developed from a collection of medical reports. This, as well as similar work discussed below such as BIRADS UMLS, SNOMED, are useful in converting clinician notes as free text into some form of structured codes for medical diagnosis purposes. They use natural language parsers and a domain vocabulary (knowledge base) developed either using a corpus or stored expert knowledge.

The gold standard in text mining is natural language processing, which aims to include semantic information in the text mining task. The full realization of this goal is still on the distant horizon however serious efforts have already achieved some success. These include AQUA, PROTEUS-BIO, and SemRep. AQUA (A Query Analyzer) is an underspecified semantic interpreter that was originally formulated for processing MEDLINE queries. PROTEUS-BIO applies to web documents on infectious disease outbreaks. It mines semantic predications relevant to this domain and stores them in a database. The database is then available to users. SemRep is being developed to recover semantic propositions from biomedical research literature. It again focuses on MEDLINE citations. SemRep utilizes underspecified syntactic analysis and structured domain knowledge. In addition to investigations that consider semantics, non semantic approaches are yielding significant progress as well. Vector space models, neural networks, kernel methods, decision trees and rule induction, and probabilistic models are all being used for classification without strong emphasis on semantic characteristics and are yielding promising and interesting results as applied to text mining.

BACKGROUND

The advent of computed tomography (CT) has revolutionized diagnostic radiology (Figure 1). Since the inception of CT in the 1970s, its use has increased rapidly. It is estimated that more than 62 million CT scans per year are currently obtained in the United States, including at least 4 million for children (Brenner & Hall, 2007). The increase in the use of medical radiation, especially in diagnostic CT scanning has raised many concerns over the possible adverse effects of procedures conducted in the absence of any serious risk/benefit analysis, especially where these procedures are carried out on Children (UNSCEAR, 2000). According to a survey conducted in 1996 (White, 1996) the number of CT scanners per 1 million population was 26 in the United States and 64 in Japan. The growth of CT use in children has been driven primarily by the decrease in the time needed to perform a scan — now less than 1 second — largely eliminating the need for anesthesia to prevent the child from moving during image acquisition (Frush et al, 2003). Overuse of diagnostic CT radiation, which deliver radiation doses 50 to 200 times higher than most X-rays, can lead to an increased risk of cancer. Additionally, it may lead to an unnecessary rise in health care costs (Roebuck, 1999; Ghotbi et al, 2005; Walsh, 2004).

In this system a motorized table moves the patient through the CT imaging system. At the same time, a source of x-rays rotates within the circular opening, and a set of x-ray detectors rotates in synchrony on the far side of the patient. The x-ray source produces a narrow, fan-shaped beam, with widths ranging from 1 to 20 mm. In axial CT, which is commonly used for head scans, the table is stationary during a rotation, after which it is moved along for the next slice. In helical CT, which is commonly used for body scans, the table moves continuously as the x-ray source and detectors rotate, producing a spiral or helical scan. The illustration shows a single row of detectors, but current machines typically have multiple rows of

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