Clinical Decision Making System

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1. Introduction

Healthcare informatics is one of the applications of semantic computing. Healthcare organizations are tasked with developing metrics for measuring quality in terms of results, patient experience, workflow efficiency, access and organization. Electronic Health Records (EHRs) is the storage to capture data routinely generated as part of standard of care is yielding. An ongoing challenge is how to effectively apply high-dimensional and unstructured dataset to support clinical decision making and improve resource management. This paper is aims to optimize the expert selection procedure by Clinical Decision Support System (CDSS). The selection procedure is based on the context of patients such as patient’s health condition, age gender, previous treatments and so forth. This paper develops algorithms that use semantic knowledge about the patient to assess and recommend expertise with the goal of optimizing the process for selecting an expert.

The diagnostic accuracy of an expert is depends on the contexts of patient. All information in the context to the patient that can be utilized in the decision making process. We propose in this paper learns the most relevant context is the current health condition of the patient and use s to estimate the level of expertise exhibited by the expert. The level of expertise is defined based on the accuracy of their diagnosis. The different clinics have healthcare professionals with different expertise and some of these clinics may have access to CDSSs from different manufacturers and of different types while some others just rely on human experts. In the proposed system, these clinics can cooperate with each other to improve diagnostic accuracy by learning the contextual specializations of the other clinics.

Based on the context of the patient, the expert selection strategy updated every time after the health condition of the patient is revealed. Based on this feedback, the diagnostic accuracy of the chosen expert is updated. The patients can provide the feedback to the expert, clinic, and facilities to evaluate the success rate of CDSS. The expert selection procedure is based on scoring of the expert taken by the feedback of patients. To select an expert we provide scoring of experts. Additionally, symptoms of certain patients and facilities of clinics are the other criteria for the expert selection procedure. This criterion is known as Convergence Criteria is to optimizing selection of a best expert to the patient.

2. About The System

PAY-FOR-PERFORMANCE programs are now firmly ensconced in the payment systems of US public and private insurers across the spectrum. More than half of commercial health maintenance organizations are using pay-for-performance, and recent legislation requires Centers for Medicare & Medicaid Services (CMS) to adopt this approach for Medicare. As commercial programs have evolved during the last 5 years, the categories of providers (clinicians, hospitals, and other health care facilities), numbers of measures, and dollar amounts at risk have increased. In addition, acceptance of performance measurement among physicians and organized medicine has broadened, with the American Medical Association committing to the US Congress in February 2006 that it would develop more than 100 performance measures by the end of 2006. To date, widespread experimentation has yielded important lessons and highlighted critical challenges to paying for performance. Several recently published evaluations have demonstrated both the potential of pay-for-performance and the need for careful design of programs to ensure their effectiveness. While recognizing the shortcomings of current pay-for-performance programs, it is critical to reaffirm what most physicians and health care purchasers alike believe: the current payment system thwarts high-quality care and needs to be reformed. Furthermore, the basic intent of pay-for-performance— to encourage and assist providers in offering the most clinically appropriate care—would be a positive step from the current payment system. Nonetheless, there are many details about how pay-for-performance would actually be
implemented that could mitigate or even reverse some of its good intent. Our objective is to review dimensions of pay-for-performance programs that economic theory or available data suggest would be important determinants of their influence. With CMS poised to enter the fray and many commercial payers evaluating, expanding, and updating their first-generation pay-for-performance programs, the time is right to examine critically the various approaches to pay for performance.

Some pay-for-performance schemes have paid as little as $2 per patient and had an impact, while others offering bonuses of up to $10,000 to a practice had no effect. No specific dollar amount or percentage will be the right amount for every circumstance. Economic theory suggests that the reward should be commensurate with the incremental cost of the quality improvement required, including the lost revenue that the provider could generate in other activities, such as seeing more patients. In addition, although most current pay-for-performance programs offer only one kind of payment, such as a bonus for achieving 90% influenza vaccination rates, it will be more effective to vary the payment approach according to the stream of costs that adherence creates. The introduction of performance incentives likely will influence which areas of practice are targeted for quality improvement efforts. Therefore, providers should seek a central role in deciding what is measured. Furthermore, appropriate measurement of clinical performance is not always intuitive; therefore, physicians also need technical input to determine precisely how performance is assessed.

First generation pay-for-performance programs have largely been designed to identify and reward top performers, by doing so directly (eg, bonuses are paid only to hospitals that perform in the top quartile for a measure), by allowing providers to voluntarily self-select into the program, or by setting and rewarding standards of performance that are achievable only by a few. Many current pay-for-performance programs offer rewards for high relative performance (eg, being among the top 10% of physicians) rather than absolute performance. Rewarding only the top providers creates competition and can stretch a small bonus pool. On the other hand, competition may limit collaboration and sharing of best practices and may create or sustain quality gaps between high- and low performing providers. Furthermore, this “tournament” approach introduces uncertainty—because a physician’s bonus depends not only on his or her performance but also on that of the rest of the network. If they are uncertain about how much additional revenue they can get, providers may be unwilling or unable to make investments in quality improvement. Because reducing disparities in health and health care quality is a national priority, this issue deserves explicit attention in the design of pay-for-performance. One approach could be to offer larger incremental payments for providing high-quality care to populations that are disadvantaged or more costly to treat effectively. One argument for higher payments is that the costs of improving care will be greater for some providers because of their patients’ geographic, linguistic, educational, financial, and other barriers. Alternatively, capital grants, technical assistance, or special training (eg, in cultural competence) could be provided to hospitals and physicians who treat disadvantaged patients under pay-for-performance contracts. If low patient adherence is a major barrier to quality improvement in some populations, a case may be made for offering patients a parallel incentive or assistance programs. Health plans and large employers can and do offer patients cash awards or gifts for healthy behavior, nurse help lines, case- and disease management, and educational materials, and these programs could be integrated with pay-for-performance to reduce the barriers to high provider performance.

**ELECTRONIC HEALTH RECORDS (EHRs)** provide a centralized location for aggregating patient data acquired from different sources and at multiple biological scales, with the aim of making this data readily accessible to healthcare professionals. While an intent of digitizing health records has been to lower the cost of healthcare, reduce the number of preventable medical errors, and improve the accuracy of diagnosing and treating patients, the sheer amount of data collected poses new challenges. Physicians often need to strike a balance between managing a large number of patient cases and spending sufficient time to thoroughly review a patient’s medical history. A study showed that the volume of work associated with primary care visits has increased, resulting in a shorter amount of time available to address individual tasks such as diagnosing patients, prescribing medications, ordering procedures, and providing counseling or physical therapy. Today, a comprehensive review of the patient’s health record would require a clinician to examine documents, medical images, and charts while mentally noting issues related to the current clinical context—all while disregarding unrelated information contained within the presented electronic record. Given their time constraints, clinicians are limited in their abilities to process all of this data simultaneously. As such, much of their time is spent skimming parts of the patient record until useful information is found. This problem is compounded by the addition of new information derived from genomic analyses, which provide additional evidence that needs to be understood and interpreted in the context of the entire patient record.
In current EHR implementations, results and interpretations are often scattered across different parts of the user interface, requiring a user to navigate through multiple screens to find relevant information. For example, if a neuro-oncologist wishes to determine if her patient is eligible for a clinical trial, she would need to review multiple documents such as oncology reports (family/treatment history), oncology consults (Karnofsky performance status), radiology reports (evidence of tumor progression), pathology reports (grade, histological type), and laboratory results (e.g., serum creatinine levels). As EHRs become the primary repository for all clinical data generated, adapting the presentation of this data to different users becomes more important. Unique views of patient data can be created to meet the information needs of each user. A concise presentation that integrates relevant information across all available sources and displays only the necessary details would not only help practitioners reduce the time spent searching for relevant data but also assist them to utilize this data more effectively to inform personalized care and medical decision-making.

**SEMANTIC COMPUTING** - The results demonstrate the feasibility of this approach; such an AI framework easily outperforms the current treatment-as-usual (TAU) case-rate/fee-for-service models of healthcare. The cost per unit of outcome change (CPUC) was $189 vs. $497 for AI vs. TAU (where lower is considered optimal) – while at the same time the AI approach could obtain a 30–35% increase in patient outcomes. Tweaking certain AI model parameters could further enhance this advantage, obtaining approximately 50% more improvement (outcome change) for roughly half the costs.

The connection between content and the user can be made via (1) semantic analysis, which analyzes content with the goal of converting it to a description (semantics); (2) semantic integration, which integrates content and semantics from multiple sources; (3) semantic services, which utilize content and semantics to solve problems; and (4) service integration, which integrates different kinds of service to provide more powerful services; and (5) semantic interface, which attempts to interpret naturally expressed user intentions. The reverse connection converts descriptions of user intentions to create content of various sorts via techniques of analysis and synthesis. Note that as most of the information is sent and received through a network, security is needed at multiple levels including data - level, communication level, database level, application level and system (community) level. The flows of information are controlled both horizontally and vertically to assure desirable properties including QoS (quality of services) and integrity.

1. Semantic Analysis — analyzes and converts signals such as pixels and words (content) to meanings (semantics).
2. Semantic Integration — integrates the content and semantics from different sources with a unified model; it also includes languages and methodologies needed for developing semantic applications.
3. Semantic Services — utilize the content and semantics to solve problems, and some applications may be made available to other applications as services.
4. Service Integration — integrates different services to provide more powerful service.
5. Semantic Interface — allows the user intentions to be described in a natural form

**ARTIFICIAL INTELLIGENCE FRAMEWORK FOR SIMULATING CLINICAL DECISION-MAKING**

**Objective**—In the modern healthcare system, rapidly expanding costs or complexity, the growing countless of treatment options, and exploding information streams that often do not effectively reach the front lines hinder the ability to choose optimal treatment decisions over time. The goal in this paper is to develop a general purpose (non-disease-specific) computational/artificial intelligence (AI) framework to address these challenges. This framework serves two potential functions: (1) a simulation environment for exploring various healthcare policies, payment methodologies, etc., and (2) the basis for clinical artificial intelligence – an AI that can “think like a doctor”.

**Methods**—This approach combines Markov decision processes and dynamic decision networks to learn from clinical data and develop complex plans via simulation of alternative sequential decision paths while capturing the sometimes conflicting, sometimes synergistic interactions of various components in the healthcare system. It can operate in partially observable environments (in the case of missing observations or data) by maintaining belief states about patient health status and functions as an online agent that plans and replans as actions are performed and new observations are obtained. This framework was evaluated using real patient data from an electronic health record. Results—The results demonstrate the feasibility of this approach; such an AI framework easily outperforms the current treatment-as-usual (TAU) case-rate/fee-for-service models of healthcare. The cost per unit of outcome change...
(CPUC) was $189 vs. $497 for AI vs. TAU (where lower is considered optimal) – while at the same time the AI approach could obtain a 30–35% increase in patient outcomes. Tweaking certain AI model parameters could further enhance this advantage, obtaining approximately 50% more improvement (outcome change) for roughly half the costs. Conclusion-Given careful design and problem formulation, an AI simulation framework can approximate optimal decisions even in complex and uncertain environments. Future work is described that outlines potential lines of research and integration of machine learning algorithms for personalized medicine.

3. Future Enhancement
- The application can be enhanced to mine information on disease history.
- Clustering algorithm can be applied to group patients based on their observation parameters.
- K means clustering algorithm can be applied to generate user communities.

4. Conclusion

The Centralized decision support system that select from CDSS (Clinical Decision Support System) and a set of human expert to make diagnosis recommendations. The expert selection system is working on the basis of the information about the patient. We prove that the diagnostic accuracy of the proposed system converges to the accuracy of the best expert, which means that the best diagnosis mechanism (whether a human expert or a CDSS) for each context is perfectly learned. Moreover, the proposed algorithm selection model (LEX) learns the best expert for treating a patient with a specific context with a clinic; hence, its performance is better than the performance of the best expert within any given clinic. Here a top admin is present whose person co-ordinate the entire authentication process. It provides the security of the proposed system. It also provides a blood bank facility which helps the patient for getting available blood group from the nearest place. The future works include it can be enhanced to mine information on disease history, Clustering algorithm can be applied to group patients based on their observation parameters and K means clustering algorithm can be applied to generate user communities.

5. References


