

MALNUTRITION RECOMMENDATION OF DOCTOR USING PREFERENCE LEARNING ALGORITHM

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Abstract- Web-based appointment systems are emerging in healthcare industry providing patients with convenient and diversiform services, among which physician recommendation is becoming more and more popular tool to make assignments of physicians to patients. Motivated by a popular physician recommendation application on a web-based appointment system in China, this paper gives a pioneer work in modeling and solving the physician recommendation problem. The application delivers personalized recommendations of physician assortments to patients with heterogeneous illness conditions, and then, patients would select one physician for appointment according to their preferences. Capturing patient preferences is essential for physician recommendation delivery; however, it is also challenging due to the lack of data on patient preferences. In this project, we formulate the physician recommendation problem based on which the preference learning algorithm is proposed that optimizes the recommendations and learns patient preferences at the same time. Since the illness conditions of patients are heterogeneous, the algorithm aims to make personalized recommendation for each patient. Besides demonstrating the effectiveness of algorithm performance in terms of regret bound, we also provide extensive numerical experiments to show the expected algorithm performance under heterogeneous reward scenarios and performance comparison with algorithms in the literature under fixed reward scenarios.

We introduce the flexibility of adjusting preference estimate update interval into our algorithm and conclude that short update interval contributes to short-term performance while long

update interval leads to good results in the long run. Furthermore, we analyze how preference bound helps the algorithm to make explorations, which constitute two major contributions of our algorithm. Finally, we discuss the relevance between patient preferences and physician utilization and present a utilization-balancing approach that is effective in numerical experiments.

Keyword— *Dynamic policy, patient preference learning, physician recommendation*

I INTRODUCTION

The development of information technology has promoted a wide range of web-based applications, such as e-commerce, online booking of airline and hotel, as well as online services in healthcare industry. For example, [1] models and analyses the electronic visits in primary care, and [2] and [3] study web-based appointment systems. Well-known web-based or mobile-based healthcare applications include ZocDoc, Quest Diagnostics, as well as WeDoctor and HaoDF in China, and these systems are gatherings of a huge number of resources, i.e., physicians, from different hospitals of different areas. According to some observations in industry, patients are not able to find the most suitable physicians for their illness condition because of their lack of appropriate medical knowledge. To that end, physician recommendation becomes an effective tool on web- or mobile-based applications to assign adequate resources to patients, which are the motivation of this paper. Generally speaking, these applications provide appointment services to patients through physician assortment recommendations from which patients select one for medical services. Specifically to start with the service, patients need to first select the favoured hospital location, appointment time

II. LITERATURE SURVEY

- 1) Paper Name- Combining Traditional Learning and the E-Learning Methods in Higher Distance Education: Assessing Learners' Preference

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Description:

Distance Education is a system where learners are separated from the teachers or educational institution both in time and space for a reasonable period of their learning. It may include contact, no contact and part-time education (Federal Republic of Nigeria, FRN 2004). The concept of Distance Education in higher institutions is no longer new to most nations around the world. It has been found as a viable and pragmatic alternative in the educational delivery process especially at the tertiary level. In Nigeria, it has been accepted and integrated into the mainstream of the Nigerian educational system (Akpan, 2008). What is new however is that different strategies and methods of instructional delivery for meaningful learning kept evolving. Concepts like blended learning, flexible learning, and virtual learning amongst others abound. The question on the lips of practitioners becomes 'is there one best method of delivery?' This we opine may meet divergent views depending on the sociocultural factors predominant in a particular region or nation.

2) Paper Name- Considering data-mining techniques in user preference learning

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Description-

Preference learning has been of major interest in past years. A lot of attention was focused in the developing of user models and preferences. However, the use of classical machine learning methods, especially data mining methods, has not been widely discussed. In this paper we present a simplified model, which abstracts from user inconsistencies and gradual changing his/her preferences. As a motivation example, we consider an example of a user looking for a notebook. We present him/her with a small sample of notebooks (we do not discuss the problem of the sample creation here; it was discussed in [1]). We ask him/her to evaluate notebooks with the following five values (they can be numeric, linguistic, pictorial choices – we do not discuss HCI aspects here):

3) Paper Name- Discriminative apprenticeship learning with both preference and non-preference behavior

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Description-

In traditional framework of learning from

demonstration, an apprentice just attempts to mimic a demonstrator's behavior inflexibly without understanding the inner mechanism underlying demonstrated behavior. This leads to one problem in robotics that while modern robots are physically capable of performing many useful tasks, they are only able to perform the same tasks repeatedly in constant environment. To achieve adaptive ability, reinforcement learning (RL) is widely used in robotics area, and turns out to be a suitable technique under a given reward that is usually constructed manually in advance. In many cases, however, constructing such a reward remains to be not only tedious but also difficult to encode explicitly. Faced with such a problem, taking the goal of recovering the reward function according to the demonstrated behavior, inverse reinforcement learning framework is then studied. An widely cited work that first formalizing the inverse reinforcement learning was carried out by Ng & Russell [1], based on which, the apprentice first recovers the reward function from demonstrations and then uses it to find a desired behavior. However, it is ill-posed, since a large class of reward functions might lead to the same optimal behavior, meanwhile many optimal behaviors could be found under the same reward function. Most works have been proposed to alleviate this problem, including Maximum Margin Planning (MMP) [2], Bayesian approach [3] and Maximum Entropy algorithm [4], etc.

4) Paper Name- Pairwise Kernel-Based Preference Learning for Multiple Criteria Decision Making

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Description-

One of the main problems in the theory and practice of decision-making is to construct a complex generalized index, combining the set of particular criteria [1, 2]. This problem occurs in the problems of multi-criteria optimization based on different ways of aggregating the particular criteria [3], in optimal ordering or ranking of objects based on their features [4, 5] and a number of other practical applications. It is assumed that a set of features describes the objects performance or quality according to some criteria. The most common and effective approach to solving such problems is based on the so-called preference or utility functions, a scalar real-valued function which reflects a decision-making preference with respect to particular criteria or features [6]. In decision making processes preference function may be used for construction of aggregate performance index of objects (alternatives) over for all criteria, which, in fact, is an expert measure of object's performance.

5) Paper Name- Electronic Visits in Primary Care: Modeling, Analysis, and Scheduling Policies

Author- Xiang Zhong, Jingshan Li, *Senior Member, IEEE*, Philip A. Bain, and Albert J. Musa

Description-

The rapid development of information technology has made the delivery of healthcare over a distance possible, which introduces substantial opportunities. Many healthcare organizations have introduced online electronic visit programs, referred to as e-visit (or e-portal, e-service, and so on), to provide the patient-physician communication through securing messages [5]. Recent studies demonstrate that by introducing e-visits, significant savings can be obtained with improved access to care, and increased provider efficiency and patient satisfaction [6]–[10]. To better understand and implement e-visits, a mathematical model of primary care delivery through both the office and the e-visits is aspired. It can provide the care delivery process a fresh look from an integrated systems’ engineering perspective. However, few quantitative models on e-visits are available in the current literature. How primary care physicians manage their operations in response to the introduction of e-visits is still an open question. Therefore, this paper is devoted to developing an analytical tool to investigate e-visit’s impact on physician’s practice, and identify the conditions that e-visits can improve patient accessibili

III. PROPOSED METHODOLOGY:

A. PROPOSED-SYSTEM ARCHITECTURE

Finding frequent item sets in a dataset for Boolean association rule. Name of the algorithm is Apriori because it uses prior knowledge of frequent item set properties. We apply an iterative approach or level-wise search where k-frequent item sets are used to find k+1 item sets. To improve the efficiency of level-wise generation of frequent item sets, an important property is used called Apriori property which helps by reducing the search space. The senior population with chronic diseases, and substantially reduce the cost of care [6]–[10]. Additional studies investigate the issues such as billing and reimbursement, information system structures, legal and regulatory issues, financial return, and system implementation, and training [5]. As a quantitative analysis of e-visits, a patient health dynamics model is developed in [12] under the alternative primary care delivery mode, which includes

the usage of e-visits and nonphysician providers. This paper quantifies the overall impact of adopting e-visits on physician’s choices and expected earnings and patients’ expected health outcomes. In a follow-up study based on these results, it is argued that e-visits provide a gateway for transforming traditional primary care delivery [26].

B ALGORITHM: Apriori Algorithm

All non-empty subset of frequent itemset must be frequent. The key concept of Apriori algorithm is its anti-monotonicity of support measure. Apriori assumes that Before we start understanding the algorithm, go through some definitions which are explained in my previous post. Consider the following dataset and we will find frequent itemsets and generate association rules for them

Id	Frequent match Item
Sympton1(I1)	4
Sympton2(I2)	5
Sympton3(I3)	3
Sympton4(I4)	5
Symptoms5(I5)	6

Table 1: Frequent Items matched

Minimum support count =3
 minimum confidence is 60%

Confidence

Confidence(A-

>B)=Support_count(AUB)/Support_count(A)

So here, by taking an example of any frequent itemset, we will show the rule generation.

Itemset {I1, I2, I3} //from L3

SO rules can be

$$[I1 \wedge I2] \Rightarrow [I3] \text{ //confidence} = \frac{\text{sup}(I1 \wedge I2 \wedge I3)}{\text{sup}(I1 \wedge I2)} = \frac{2}{4} * 100 = 50\%$$

$$[I1 \wedge I3] \Rightarrow [I2] \text{ //confidence} = \frac{\text{sup}(I1 \wedge I2 \wedge I3)}{\text{sup}(I1 \wedge I3)} = \frac{2}{4} * 100 = 50\%$$

$$[I2 \wedge I3] \Rightarrow [I1] \text{ //confidence} = \frac{\text{sup}(I1 \wedge I2 \wedge I3)}{\text{sup}(I2 \wedge I3)} = \frac{2}{4} * 100 = 50\%$$

$$[I1] \Rightarrow [I2 \wedge I3] \text{ //confidence} = \frac{\text{sup}(I1 \wedge I2 \wedge I3)}{\text{sup}(I1)} = \frac{2}{6} * 100 = 33\%$$

$$[I2] \Rightarrow [I1 \wedge I3] // \text{confidence} = \frac{\sup(I1 \wedge I2 \wedge I3)}{\sup(I2)} = \frac{2}{7} * 100 = 28\%$$

$$[I3] \Rightarrow [I1 \wedge I2] // \text{confidence} = \frac{\sup(I1 \wedge I2 \wedge I3)}{\sup(I3)} = \frac{2}{6} * 100 = 33\%$$

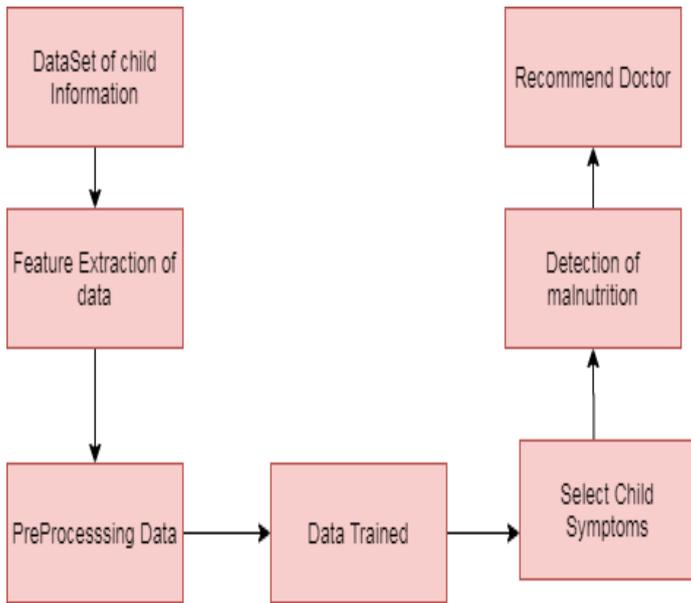


Figure 1:-System Architecture

IV.RESULTS

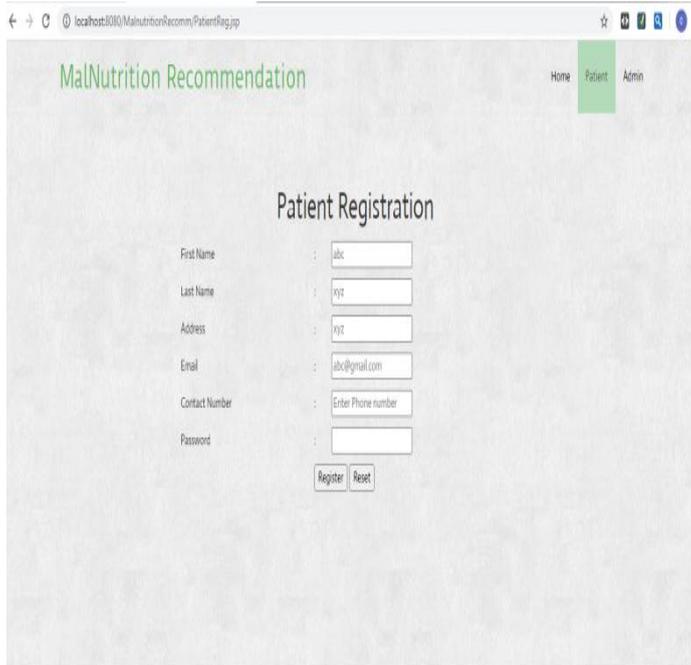


Figure 2:- Patient Register



Figure 3:-Patient Login

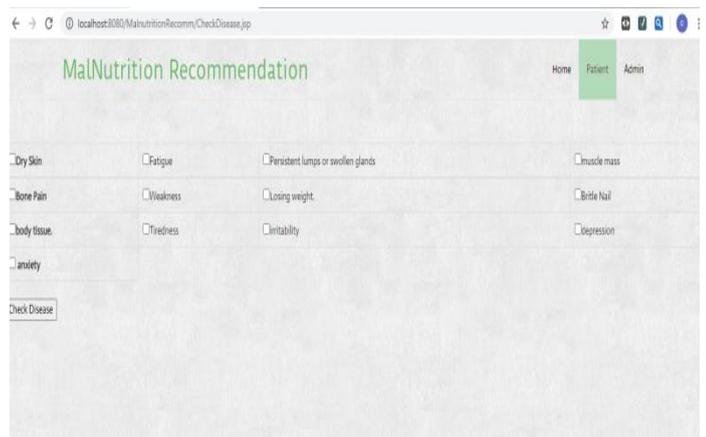


Figure 4:-Symptoms.

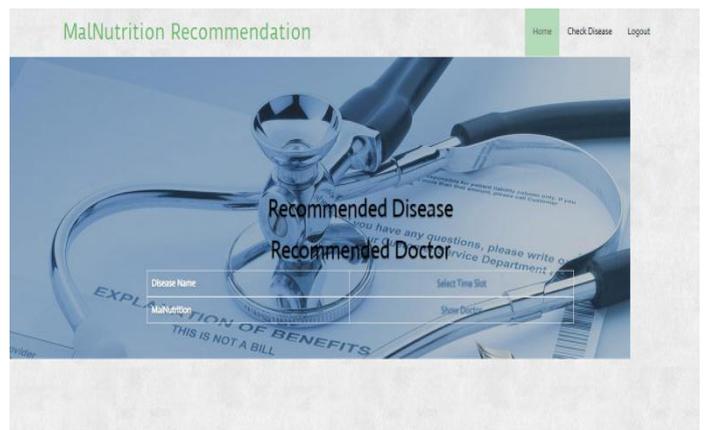


Figure 5:-Disease Prediction

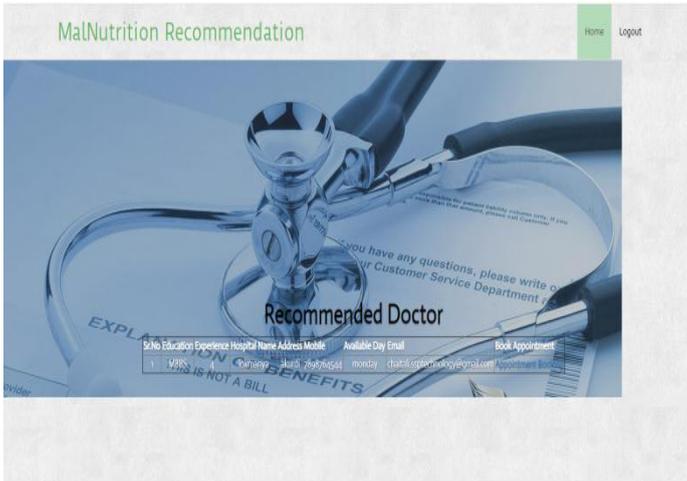


Figure 6:-Doctor_recommend

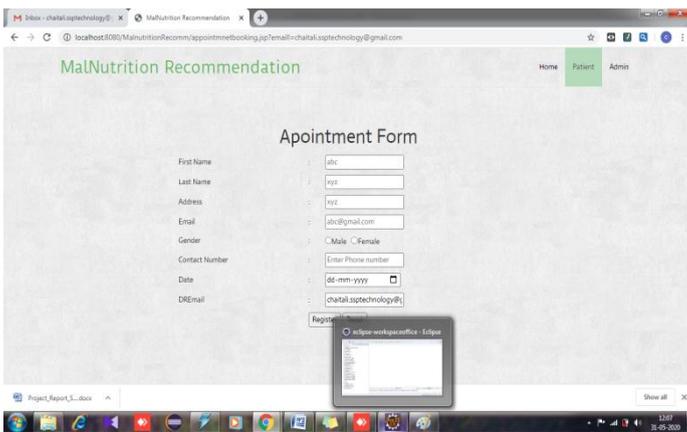


Figure 7:-Recommend. Doctor appointment

V CONCLUSION AND FUTURE WORK

Malnourishment of a child is a serious health risk and also hinders the child’s social and economic development. Although there are many programs for eradicating the malnutrition, monitoring the effectiveness of the program is a cumbersome and time consuming job. The manual nature of the current monitoring method may also induce errors in the information obtained. Proposed system will overcome these disadvantage up to certain extent and also speed up the rate of measurement due to the automated nature of the measurement. The centralized access and local storage helps to maintain the reliability of the data and protects the data from misuse. In addition to the three scheduling policies discussed in this paper, other policies, such as blocking (i.e., assign a block time to process e-visits) or alternative (i.e., switching between office and e-visits) are optional. Evaluating and comparing other scheduling policies are also of interest.

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