iJETRM
International Journal of Engineering Technology Research & Management

A REVIEW OF HEALTH RECOMMENDER SYSTEM

Mrs. Pooja Dahiya[*1]
Mrs. Reena[2]
[*1,2]Assistant Prof (Computer Science), Tika Ram PG Girls College, Sonipat

ABSTRACT

A healthcare system is required to analyze a large amount of patient data which helps to derive insights and assist the prediction of diseases This system should be intelligent in order to predict a health condition by analyzing a patient's lifestyle, physical health records and social activities. The health recommender system (HRS) is becoming an important platform for healthcare services. Technologies as data mining and recommender technologies provide possibilities to explore potential knowledge from diagnosis history records and help doctors to prescribe medication correctly to decrease medication error effectively. Data mining technologies can be applied to recommendation system resulting in medical recommender system framework which consist of database system module, data preparation module, recommendation model module, model evaluation, and data visualization module. We investigate the medicine recommendation algorithms of the SVM (Support Vector Machine), BP neural network algorithm and ID3 decision tree algorithm based on the diagnosis data. SVM can be used with an aim to provide model accuracy, model efficiency, and model scalability.

Keywords—
Recommender system, PHR, HRS, collaborative filtering, SVD

1. INTRODUCTION

Recommender system provides a platform to recommend such a product which is valuable and acceptable for people. Such a system is based on the features of the item, patient preferences and brand information. This filtering-based system collects a large amount of information dynamically from the patient's interests, ratings, choices or the item's behavior, then filters this information to provide more vital information [1,2]. Various approaches are made to retrieve large quantities of data efficiently because there are a lot of unstructured and unprocessed data that need to be processed and can be used in various applications. Data and information are spread among healthcare centers, hospitals, clinics. Beside three Vs (volume, variety, velocity), the veracity of healthcare data is also important for its role towards improving healthcare. Veracity refers to the consistency and trustworthiness of data [4,5]. A recommender system has the capability to anticipate whether a person would purchase a product or not based on the patient's preferences. This system can be implemented based on a patient's profile or an item's profile. This paper explains the item based collaborative filtering-based health recommender system which provides valuable information to patients based on the item's profile. There are many blogs and social forums accessible on the internet where people can provide opinions, reviews, blogs and different perspectives regarding products. After collecting ratings for any product by patients, the recommender system makes decisions about patients who don't give any ratings. In particular, in the sector of healthcare, choices can be life-threatening as they are concerned with the life and safety of patients. The recommender system should not only support decision making and avert dangers or failures, but it should also monitor patients and dispense treatment as necessary, keep track of vital signs and communicate in real time via a centralized server in the context of healthcare. These functions address the suitability of HRS.

2.BASIC CONCEPTS OF RECOMMENDER SYSTEMS

Patients and products play an crucial role in recommendation systems.In recommender systems, two main entities play crucial roles, namely patients and products. Patients give their preferences about certain items and these preferences must be found out of the collected data. The collected data are represented as a utility matrix which provides the value of each patient-item pair that represents the degree of preferences of that patient for specific items. In this way, the recommender engines are classified into patient-based and item-based recommender engines. In a patient-based recommender system,

iJETRM
International Journal of Engineering Technology Research & Management

patients give their choices and ratings of items [11].

There are various phases of recommendation systems:

1. Information Collection Phase: Information about patients is collected in this phase using which patient's profile is developed based on patient's behaviour, attributes, and resources accessed by the patient. A well defined patient's profile is must for proper working of recommendation system. A recommendation system is based on explicit feedback, implicit feedback and hybrid feedback. Explicit feedback takes input given by patients according to their interest on an item whereas implicit feedback takes patient preferences indirectly through observing patient behavior [1].

2. Learning Phase: This phase takes as input the information collected in former phase and processes this feedback by applying some learning algorithm to exploit the patient's features as output[1,2,13].

3. Prediction/Recommender Phase: Preferable items are recommended for patients in this phase. By analyzing feedback collected in information collection phase, a prediction can be made through the model, memory-based or observed activities of patients by the system.

3. HEALTH RECOMMENDER SYSTEM(HRS)

A health recommender system (HRS) is a specialization of an RS. In the context of an HRS, a recommendable item of interest is a piece of non-confidential, scientifically proven or at least generally accepted medical information, which in itself is not linked to an individual's medical history. However, an HRS's suggestions are driven by individualized health data such as documented in a personal health record (PHR). A PHR is an electronic application through wich individuals can access, manage and share their health information, and that of others for whom they are authorized, in a private, secure and confidential environment This source of information is considered the user profile of an recommender system.Patients can benefit if a PHR system supports them to view or act upon medical data and at the same time enables them to make informed decisions. It could also be a great value to patients if they are provided with PHR tools that enable them to communicate with caregivers in a direct way [13]. Thus, PHRS could "transform the tradition of episodic care to a more continuous communication channel between physicians and patients". HRS aims to supply it's user with medical information which is meant to be highly relevant to the medical development of the patient associated with that PHR. Related medical information may be recommended to health professionals who work on or with the given PHR but also it may be recommended to laymen inspecting their own PHR. Depending on a user's medical expertise an HRS should suggest medical information, which is comprehendable to that user.It is important to consider the system context of an HRS for a successful integration into any health related information system. A profile-based HRS component can be implemented as an extension of an existing PHR system. Data entries in a PHR database (DB) constitute the medical history of a PHR owner. Supplied with medical facts, an HRS computes a set of potentially relevant items of interest for a target user (e.g., a PHR owner or an authorized health professional). Such items originate from trustworthy health knowledge repositories and may be displayed while he/she inspects the PHR online.

Two separate use cases can be defined on the basis of expert level of a PHR user:
1. Patient as end-user: We intent to recommend only evidence-based health related content to end-users, which is obviously of high quality resulting in reduced risk to retrieve incomplete, misleading and inaccurate content. Here a lay person interacts with a HRS-enabled PHR without direct support by a physician. The system computes laymen-friendly content according to the person's long-term individual medical history. The relevant items are presented within the PHR system's user interface. By selecting the highest-ranking documents or media content a patient is empowered in terms of health information acquisition.
2. Health professional as end-user: Here health professional uses HRS to retrieve additional information for a certain case. For instance, related clinical guidelines or research articles can be computed automatically. This form of case-related information enrichment might support a physician with the process of clinical diagnostics as latest research results can be used for decision support. For the purpose of a direct handout (i.e., as a printout) to a patient when he or she is in a doctor's office for consultation laymen-friendly documents can also be retrieved Therefore, we can supply high quality information to user to cope with a certain disease.

iJETRM
International Journal of Engineering Technology Research & Management

Consumer-centric medical content:

It consists of expert-proven advisory on how to cope with a disease, disease definitions in general which support in understanding medical terminology, care plans which might prevent patients from acting against rules suggested by evidence-based medicine, hints on healthier living or diet information. All these features are found in consumer-centric content. However, critics question the quality of such content. The consider such content as being "incomplete, misleading and inaccurate" or incomplete and not evidence-based. By contrast, according to the Health on the Net (HON) Foundation a large and growing majority of Internet users are concerned about quality of health information found on the Internet.

Filtering techniques

There are three types of filtering techniques used by recommendation systems:

1. Collaborative Filtering: Collaborative filtering (CF) systems and computer-based recommendation are often related with the origin of the system called Tapestry. In Tapestry, with arbitrary text comments users were able to annotate documents and other users based on the comments of other users could then query. One of the main attribute of this system is that it allowed recommendations to be generated based on a combination of ideas of the input from many other users. Rather than filtering items based on content, making recommendations based on the opinions of like-minded users has become popularly known as collaborative filtering.

2. Content-based Filtering: According to [3] Content-based filtering (CBF) is an outgrowth and continuation of information filtering research. The objects of interest are defined by their associated features in a CBF system. For instance, text recommendation systems like the newsgroup filtering system uses the words of their texts as features. Based on the features present in objects that the user has rated, a content-based recommender learns a profile of the user"s interests which is called as "item-to-item correlation" and it derives the type of user profile depending on the learning method employed. Vector-based representations, neural nets and decision trees have all been used. Other system, in which the users rate the Web documents and assign them values from the binary "hot" and "cold" scale is [4].

3. Demographic Filtering: RS based on Demographic filtering (DF) classify users according to their demographic information and recommend services accordingly. In DF the user profiles are created by classifying users in stereotypical descriptions, representing the features of classes of users [5]. Demographic information identifies those users that like related services. Semi-trusted third parties use DF to recommend services by using data on individual users. DF creates categories of users which have similar demographic characteristics and then the cumulative buying behavior or preferences of users within these categories are being tracked. For a new user, recommendations are made by first finding which category he falls in and then the cumulative buying preferences of previous users is applied to that category which he belongs. Like collaborative techniques, demographic techniques also form "people-to-people" correlations but use dissimilar data. A collaborative and content-based technique requires a history of user ratings which is not of the kind required by Demographic approach.

4.

4. Outline of Health Recommender System

1. The software development team develops a problem statement which involves finding the objectives of the project.
2. The problem statement is succeeded by a description of the project's importance.
3. The designing team will perform a feasibility study of the project, including a technical assessment, cost estimation, and effort estimation.
5. Once the problem statement is approved, the team can move to the next stage, the project development stage where the team focuses on details of the projects. Because of the rise in project's cost in comparison to traditional ones, the team must do an economic feasibility study and explain why the project is cost-effective [12-13]. The project team should also provide background information on the problem domain as well as prior projects and research performed in this domain.
6. After that the design phase is implemented. The problem statement is broken down into a series of steps. Simultaneously, the independent and dependent variables or indicators are identified. The data sources are also identified, the data is collected, described, and transformed in preparation for data analytics. Hadoop, Cloudera tools can be used for accomplishing this task.
7. Now the models and their findings are tested and validated and presented to stakeholders for action. Implementation is a staged approach with feedback loops built in at each stage to minimize the risk of failure.

International Journal of Engineering Technology Research & Management

5. Health Recommender System Architecture

The architecture of the framework is divided into three parts (data collection, data transformation, data analysis and visualization):

1. Data collection: The data sources for the healthcare system have been categorized into (i) Structured data: organized data which has a predefined format, data type, and structure. Examples of such data include data generated from devices such as sensors, information about various diseases, their symptoms and diagnosis information, laboratory results, patient medical history, drug prescription, CT Scan, X-ray. (ii) Semi-structured data: data which does not conform to a data model but has some structure effective monitoring of patient's behavior. (iii) Unstructured data: data that has no defined structure, which may include medical prescriptions written in human languages, research notes, discharge summaries and so forth.
2. Data analysis: During this step health-specific recommendations can be generated. We should first talk about patients who will be using this domain. The end-patient of the system is medical researchers, doctors, and patients. There are other people who can benefit from the health recommender system (HRS) like pharmacists, clinicians, researchers. ***Minimizing the cost of healthcare should be the ultimate aim of these recommender systems.*** Analytical methods involve using Hadoop approach that uses MapReduce. This approach increases the speed of medical diagnosis and finding the optimal parameters for doctors so that he/she can detect the type of disease the patient is suffering and check the condition of the patient.
3. Visualization: Visualization and knowledge representation techniques are used to present the mined knowledge to the end patients. The healthiest recommender is the one that should be chosen, but sometimes topic-specific criteria play a role in evaluating a product. Data-driven approaches apply data mining and machine learning methods to extract insights from the heterogeneous data. It provides individual recommenders based on the past learning experience and the patterns extracted from clinical data. A combination of information retrieval and machine learning can be used for the medical database classification.

6.Evaluation of Health Recommender Systems

The evaluation criteria of the recommender system are very necessary to measure the strength of an HRS based on patient acceptance and satisfaction. By making system suitable for individual patients, the system can run as per patients' requirements so that patients will not face any problems, ultimately leading to better medical research. This includes patient diversity research, not just in regard to patient-specified results, but also in regard to the patient interface of a health recommender system. Common metrics used in the evaluation are:

i. Precision: The measure of retrieved instances that are relevant.

ii. Recall: The fraction of correctly recommended items that are also part of the collection of useful recommended items.

iii. F-Measure: It is a measure of a test's accuracy and is defined as the weighted harmonic mean of the precision and recall of the test.

iv. ROC-Curve: ROC Curve is a way to compare diagnostic tests. It is a plot of the true positive rate against the false positive rate. It is used to represent the relationship between sensitivity and specificity.

v. RSME: This measure defines the standard deviation of the residual errors, i.e., differences between predicted values and known values.

7. CONCLUSION

Health Recommender systems play an important role in the medical sector. Therefore, they are one of the new prevailing technologies for deriving supplementary information for a patient from healthcare data. These systems find recommended hospitals by calculating the similarity of patients' choices. In this paper an approach of integrating recommender systems into personal health records—termed health recommender system (HRS)—was outlined. A first definition of an HRS in the context of personal health record systems was presented. An HRS prototype which acts as an extension to a PHR system was discussed. Given medical facts from PHR data entries, it makes use of techniques like negation detection, spell-correction and semantic query expansion. A web-based assessment system can be implemented to make use of a group of physicians to develop the test collection which helps the experts to select laymen-friendly, recommendable documents matching a particular medical case.

7. REFERENCES

1. Wang, Y.; Hajli, N. Exploring the path to big data analytics success in healthcare. J. Bus. Res. 2017, 70, 287–299.

Babar, M.I.; Jehanzeb, M.; Ghazali, M.; Jawawi, D.N.A.; Sher, F.; Ghayyur, S.A.K. Big data survey in healthcare and a proposal for intelligent data diagnosis framework. In Proceedings of the 2016 2nd IEEE International Conference on

iJETRM
International Journal of Engineering Technology Research & Management

Computer and Communications (ICCC), Chengdu, China, 14–17 October 2016; pp. 7–12.
4. Lafta, R.; Zhang, J.; Tao, X.; Li, Y.; Tseng, V.S.; Luo, Y.; Chen, F. An intelligent recommender system based on the predictive analysis in the telehealthcare environment. Web Intell. 2016, 14, 325–336.
3. Priyadarshini, R.; Barik, R.; Dubey, H. DeepFog: Fog Computing-Based Deep Neural Architecture for Prediction of Stress Types, Diabetes and Hypertension Attacks. Computation 2018, 6, 62.
4. Martínez-Pérez, B.; De La Torre-Díez, I.; López-Coronado, M. Privacy and security in mobile health APPs: A review and recommendations. J. Med. Syst. 2015, 39, 181.
5. Mu, R.; Zeng, X.; Han, L. A Survey of Recommender Systems Based on Deep Learning. IEEE Access 2018, 6, 69009–69022.
6. Gope, J.; Jain, S.K. A survey on solving cold start problem in recommender systems. In Proceedings of the 2017 International Conference on Computing, Communication, and Automation (ICCCA), Greater Noida, India, 5–6 May 2017; pp. 133–138.
7. Jooa, J.H.; Bangb, S.W.; Parka, G.D. Implementation of a Recommender System usingAssociation Rules and Collaborative Filtering. Inf. Technol. Quant. Manag. Procedia Comput. Sci. 2016, 91, 944–952.
8. Ponnam, L.T.; Punyasamudram, S.D. Health care Recommender System using Item Based Collaborative Filtering Technique. In Proceedings of the International Conference on Emerging Trends in Engineering, Technology and Science, Pudukkottai, India, 24–26 February 2016; Volume 1, pp. 56–60.
9. Gavgani V.Z. Health Information Need and Seeking Behavior of Patients in Developing Countries' Context; an Iranian Experience. Proceedings of the 1st ACM International Health Informatics Symposium (IHI '10), ACM; New York, New York, NY, USA. 11–12 November 2010; pp. 575–579.
10. Gerber B.S., Eiser A.R. The patient-physician relationship in the Internet age: Future prospects and the research agenda. J. Med. Internet Res. 2001;3 doi: 10.2196/jmir.3.2.e15.
11. Kivits J. Informed patients and the Internet. A mediated context for consultations with health professionals. J. Health Psychol. 2006;11:269–282.
12. McMullan M. Patients using the Internet to obtain health information: How this affects the patient–health professional relationship. Patient Educ. Counsel. 2006;63:24–28. doi: 10.1016/j.pec.2005.10.006.
13. Ueckert F., Goerz M., Ataian M., Tessmann S., Prokosch H.U. Empowerment of patients and communication with health care professionals through an electronic health record. Int. J. Med.